

**NASA CONTRACTOR  
REPORT**

NASA CR-539



NASA CR-539

LOAN COPY: RETURN TO  
AFRL (PAUL) 10  
KIRTLAND AFB, N MEX

0099514



# CHARACTERIZATION OF TIME-VARYING HUMAN OPERATOR DYNAMICS

(PROJECT ICARUS)

*by G. A. Gagne and W. W. Wierwille*

*Prepared by*  
CORNELL AERONAUTICAL LABORATORY, INC.  
Buffalo, N. Y.  
*for Langley Research Center*



0099514

NASA CR-539

CHARACTERIZATION OF TIME-VARYING  
HUMAN OPERATOR DYNAMICS

(PROJECT ICARUS)

By G. A. Gagne and W. W. Wierwille

Distribution of this report is provided in the interest of information exchange. Responsibility for the contents resides in the author or organization that prepared it.

Prepared under Contract No. NAS 1-4920 by  
CORNELL AERONAUTICAL LABORATORY, INC.  
Buffalo, N.Y.

for Langley Research Center

NATIONAL AERONAUTICS AND SPACE ADMINISTRATION

---

For sale by the Clearinghouse for Federal Scientific and Technical Information  
Springfield, Virginia 22151 - Price \$3.00



## CONTENTS

I.	INTRODUCTION . . . . .	1
II.	APPLICATION OF DETERMINISTIC CHARACTERIZATION THEORY . . . . .	10
III.	DESIGN OF THE EXPERIMENTAL FACILITY . . . . .	23
IV.	TIME-VARYING ANALYSIS OF THE TRACKING DATA . . .	33
V.	LOGIC MODEL STUDY OF TRACKING DATA . . . . .	67
VI.	CONCLUSIONS AND RECOMMENDATIONS . . . . .	75
	REFERENCES . . . . .	82

## ACKNOWLEDGEMENTS

On 25 March 1965, a project sponsored by the NASA Langley Research Center, Hampton, Virginia, was initiated with Cornell Aeronautical Laboratory to conduct experimental and theoretical investigations of human operator dynamics in compensatory systems. The work was performed mainly by the Avionics Department of the Laboratory.

The authors also wish to acknowledge the help and encouragement of the personnel of the Avionics Department of CAL, particularly Dr. William C. Schultz for his technical and administrative guidance and Mr. James R. Knight who participated in the experimental work and data interpretation on this project. Thanks are due to the experimental test pilots of CAL's Flight Research Department who willingly endured the experiment. In particular they wish to thank Mr. G. Bull, who contributed the individual data, for his suggestions and conscientious efforts.

## I. INTRODUCTION

On 25 March 1965, a project sponsored by the NASA Langley Research Center, Hampton, Virginia, was initiated with Cornell Aeronautical Laboratory (CAL) to conduct experimental and theoretical investigations with the objectives of applying and extending the deterministic theory of time-varying human operator characterization. In the six-month study, CAL has applied the deterministic characterization theory developed on the previous project (NAS 1-3485) to study pilots in the performance of both single-axis and two-axis compensatory tracking tasks with a variety of displays. Descriptions of the theoretical extensions, experimental results, and conclusions of this study are all included in this document.

### Previous Work

More than a decade has passed since the first attempt was made to mathematically model a pilot or human operator in a control system. Since that time a continual effort has been made to improve and refine both the mathematical modeling of the human operator and the application of these models to manual control system design. The investigation that has been performed under the present contract has been aimed at improving models of the human operator and at gaining an improved understanding of the human

operator's strategy and response mechanism while operating as an element in a control task.

The problem of modeling the human pilot in a control system with a high degree of accuracy is a difficult one. The difficulty arises from many causes, including the fact that the human operator exhibits both time-varying and nonlinear behavior. Thus, linear constant coefficient models, while accounting for a large portion of the human operator's response, cannot in general account for the more subtle characteristics such as variation or nonlinearity in dynamics.

Time-variation and nonlinearity in the human's dynamics can be caused by numerous psychological and physical conditions. Time-variability, for example, may be the result of fatigue, learning, changes in system dynamics or disturbance signals, multiple tasks, and changes in environment. Nonlinearity may occur because of the primary desire on the human's part to minimize error, or because of actual or believed controller excursion constraints. It therefore seemed that an improved understanding of the human operator's behavior could be attained if a theory and method were developed that would allow characterization of the human operator on a time-varying and nonlinear basis. This theory was developed and experimentally verified under NASA Langley contract NAS1-3485, and is fully described in References 1,2. A review of this theory, as it applies to the study conducted under the present contract, is found in Chapter II of this report.

It is true that some studies of the time-varying dynamics of human operators have been performed previously by other investigators<sup>3,4,5</sup>. However, it is believed that these previous studies were concerned with somewhat slower changing human dynamics than those which are investigated

herein. Moreover, to the best of the authors' knowledge, no systematic nonlinear synthesis techniques have ever been applied to human operator characterization previously.

### Problem Statement

The problem that was chosen for investigation under this contract involved the determination of linear time-varying, nonlinear time-varying and nonlinear constant coefficient models of the human operator in a tracking task. The linear time-varying models were obtained for subjects performing tracking tasks with various one- and two-axis displays with corresponding one- and two-axis dynamics. The follow-up dynamics were kept the same for all experiments and were identical in both axes. They were chosen so as to be similar to the pitch and roll dynamics of a jet fighter aircraft.

The primary objective of the experiment was to characterize the human operator involved in the above described tasks using the deterministic time-varying characterization theory, and then to use these characterizations to devise a set of rules by which each human operator responds to the displayed signals. Particular emphasis was to be placed upon determining the causes of the time-variations in the transfer characteristics.

A secondary object of the experiment was to study the nonlinearity of the human operators and to attempt the development of what might be termed a "logic model" of the operators. A logic model may be considered as a nonlinear model of the human operator that simulates the logic strategy that the operator may exhibit while tracking in a control system.



## Experimental Procedure

Because of the complexity and difficulty inherent in attempting to solve the above stated problem, a very carefully planned experiment had to be conducted. The planning of the experiment, analysis of data, and study of the results were indeed carefully worked out in detail at the beginning of the program so that they could all be completed within the rather limited scope of effort and time available. Questions as to why certain problems were not studied in greater detail or why peripheral ideas that appeared promising were not investigated can almost universally be answered by the statement that the scope of the effort did not permit further study.

The experiment itself was designed so that accurate and reliable records of the human operator's simultaneous input and output signals in the various tracking tasks could be obtained. Experienced pilots were used as primary subjects because the information gained from this study is more likely to be applied to that class of vehicular control systems wherein pilots are used. Problems of task learning and subject adaptation to the tracking system were also reduced by the use of trained pilots.

In order to permit direct comparisons between responses of different operators or even comparisons between runs for the same operator, it was essential that experimental variables be kept under close control. The experimental conditions deemed necessary for effecting this control were:

1. Performance of the tracking tasks in a relatively isolated enclosure to minimize the effects of external disturbances that might have physical or psychological effects.

2. The use of prerecorded random signals for each control axis. This procedure ensured that identical input signals were used for each run by every subject. The possibility of input signals being memorized by an operator was negligible because of the sizable time duration of the random signal, and because of the nature of compensatory tracking which would require that the system input be deduced from the displayed error signal.
3. The use of control dynamics with consistent scaling of the displayed signals for each task and subject.
4. Careful screening and selection of experimental subjects sympathetic to the objectives of the experiment to ensure reliability of the data and to reduce extraneous intersubject variations.

In any experiment involving humans, it is highly desirable to extend the experiment to include as large a number of subjects as possible in order to develop statistical confidence in the ensemble. However, because of limitations in the scope of this study, it was not possible to include a large number of subjects for each task. The quantity of data generated for a single subject is large and the cost of processing the data is high. Consequently, four subjects were selected: three pilot-engineers from the CAL Flight Research Department and a non-pilot research engineer from the CAL Avionics Department. The purpose of including the research engineer in the experiment was to obtain first-hand information regarding the nature of the tracking experiment and to provide intuitive insight into the behavioral mechanisms of human operator tracking.

The experiment was planned so that two distinctly different types of models could be obtained: those of an individual pilot, and those of an ensemble\* of four operators participating in the experiment. The objective in computing the transfer characteristics of the individual pilot was to determine the types of time variations obtained and then to study them in detail. The objective in computing the ensemble characteristic\*\* was to minimize any unusual short-term effect of a single operator on the data by averaging the effect. Since four subjects were used for the experiment, an unusual effect of any single operator may be considered as attenuated by a factor of four. Since precisely the same, synchronized input signal was used for each operator, signal-dependent time variations, if any, should be more clearly evidenced by the ensemble transfer characteristics.

The same pilot was used for analysis of "individual" data for all tasks. This pilot is one of CAL's most experienced test pilots, who has been working with variable stability aircraft and is experienced with handling qualities research. He is a member of the American Society of Experimental Test Pilots and was enthusiastic about the experiments performed on this project.

---

\* The word ensemble is used loosely herein, since only four subjects participated in the data gathering portion of the experiment.

\*\* In the generation of the ensemble data the raw error signal data were averaged over the group of subjects, and the control stick raw output data were similarly averaged. Accordingly, a composite input signal and composite output signal were obtained which were then analyzed. There was some question as to whether to average the raw data or to average the individual time-varying transfer characteristics. It was decided that, because peculiar individual variations in any signal were considered undesirable, that the raw data averaging approach would be used.

Observation of this pilot through the one-way glass system showed him to be highly attentive.

With the selection of a small number of subjects, it became important to design the experiment so as to control the effects of variables such as learning and fatigue, especially when each subject performed each of the tasks. This was accomplished by permutating the order of subjects and tasks and ensuring that each subject was well practiced in each task. In this way, the undesirable effects of a limited number of subjects on the ensemble data were effectively minimized. Of course, permutating the order of the subjects is only possible when gathering ensemble data. In the individual pilot case, the assumption must be made that the incremental learning after a significant amount of practice becomes negligible, and that the rest periods between runs are sufficient to avoid fatigue.

The different tracking tasks that were performed by each subject in the experiment are defined as:

Task 0 - Subject tracked a random signal independently in pitch using a cathode ray tube displaying the tracking error as a proportional vertical displacement of a dot from the center of the tube face. Single-axis data for the roll axis was then obtained by repeating the experiment using the roll axis only.

Task 1 - Subject simultaneously tracked random signals in both pitch and roll axes using a cathode ray tube as a display. Tracking errors were indicated by the proportional vector displacement of a dot from the center of the tube face.

Task 2 - Subject simultaneously tracked random signals in pitch and roll axes, using an electronically simulated gyro-stabilized artificial horizon display (8-ball display). This display consisted of a horizontal bar whose vertical displacement from the center position was proportional to the error in the pitch axis. The roll error was displayed by a rotation of the bar, from its horizontal rest position, proportional to the sine of the error. The bar appeared to rotate about its center which was constrained to move along a vertical line bisecting the cathode ray tube face. A transparent plastic mask covering the tube face was imprinted with an aircraft symbol in order to simulate the proper relationship between the aircraft and the horizon.

Task 3 - Subject simultaneously tracked random signals in pitch and roll axes using separate panel meters as a display. The two center-zero meters mounted at right angles were separated a sufficient distance to force the operator to shift his gaze from one to the other in tracking the pitch and roll components of the error.

Task 4 - This task was similar to Task 3, except for the inclusion of a third panel meter to be monitored. The workload represented by this extra meter required the subject to activate a switch whenever the deflection of the pointer was beyond a clearly marked range. Penalties for neglecting or disregarding the workload meter were not assigned; however, direct observation

of the subjects during their performance and later inspection of the workload records provided strong indications that the subjects were conscientious.

Subjects were allowed to practice each task before a data run until reasonable tracking proficiency was attained. Tracking instructions stressed the desirability of maintaining minimum display error while avoiding excessively large and rapid control stick movements as much as possible. Each subject performed tasks for two consecutive days. Table 1 indicates the order of subjects and tasks performed in the experiment. Each data-taking run, scheduled a short time after the practice session, consisted of two minutes of warm-up tracking followed by one minute of actual data run.

Table 1  
EXPERIMENT SCHEDULE

DAY	SUBJECT A TASKS	SUBJECT B TASKS	SUBJECT C TASKS	SUBJECT D TASKS
1	0	2	3	4
	1	3	4	0
	2			1
2	3	4	0	2
	4	0	1	3
		1	2	

## II. APPLICATION OF THE DETERMINISTIC THEORY

This chapter consists of a summary of the application of the deterministic characterization theory to obtain the time-varying transfer characteristics of the human operator. A digital computer program, based on the theory, was developed to calculate the time histories of an optimal set of gains for the model shown in Figure 1. The transfer characteristics of the model, displayed as special step responses, then represent the best estimates of the actual characteristics of the human operator.

### Review of the Deterministic Characterization Theory<sup>1, 2</sup>

The essential element of the deterministic characterization theory consists of the development of an analytical technique for minimizing the integral squared error between the output of the human operator and that of a mathematical model, (a fixed form filter excited by the same input as is displayed to the human operator.) The integral squared error is minimized through the solution of a set of linear equations whose unknowns are the weighting factors for a set of fixed, known time functions making up the time-varying gains.

The theory may be used to readily determine a set of constant gains that minimize the integral squared error for a particular time interval. In this application there is no uncertainty in the computed constants, and they are optimum for the form of filter selected. If however, the desire is for a model with parameters which vary with time, then the minimization of the performance measure must be performed with constraints on the allowable time-variations in the parameters.

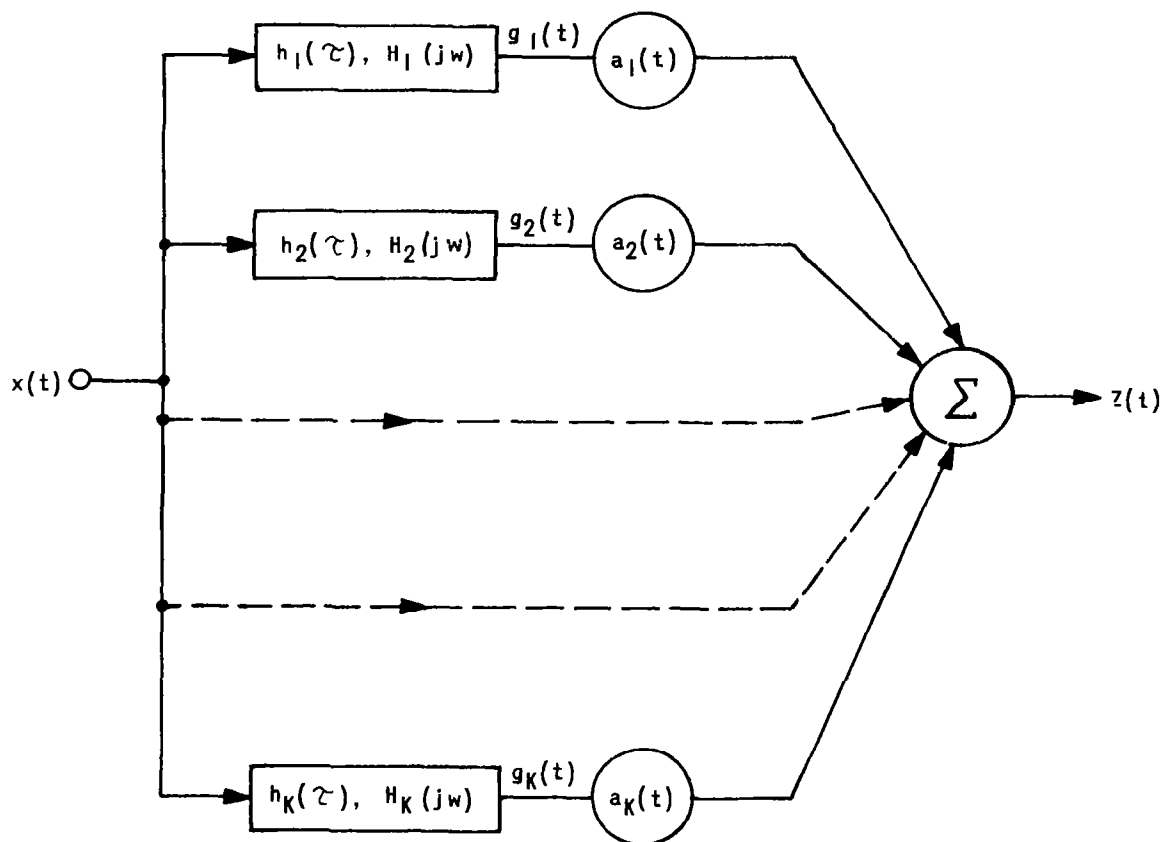


Figure 1 FIXED FORM MODEL FILTER USED TO CHARACTERIZE A HUMAN OPERATOR



The error between the output of the model of Figure 1 and that of the human operator is defined as

$$e(t) = \left[ y(t) - \sum_{i=1}^K a_i(t) g_i(t) \right] \quad (1)$$

where  $y(t)$  is the output of the human operator (stick output)  
 $g_i(t)$  is the output of  $i^{th}$  fixed component filter to the  
input signal  $x(t)$  which the human operator is tracking, and  
 $a_i(t)$  is the gain of the  $i^{th}$  component filter at time  $t$ .

The performance measure to be minimized is defined as

$$\theta = \int_0^T e^2(t) dt \quad (2)$$

where

$t = 0$  is the initial point, and

$t = T$  is the final point in the time interval over which a  
solution is desired.

A meaningful constraint for the time varying gains is one which forces the  
time-varying parameters  $a_i(t)$  to be a weighted set of fixed time functions  
 $\beta_m(t)$ . The time-varying parameters are expressed as

$$a_\ell(t) = \sum_{m=0}^L \alpha_{m\ell} \beta_m(t) \quad (3)$$

The effect of this constraint on the solution for the optimal set of gains is  
heavily dependent upon the choice of the  $\beta_m(t)$ . This point will be  
discussed after the minimization process has been described.

Substituting equations (1) and (3) into (2) yields the following expression for the performance measure.

$$\theta = \int \left[ y(t) - \sum_{i=1}^K \sum_{m=0}^L \alpha_{m\ell} \beta_m(t) q_i(t) \right]^2 dt \quad (4)$$

It can be shown that the performance measure is a quadratic (nonrotated parabolic) function of each coefficient,  $\alpha_{p\ell}$ . The critical values are obtained by equating the partial derivative of the performance measure with respect to each  $\alpha_{p\ell}$  to zero; thus

$$\frac{\partial \theta}{\partial \alpha_{p\ell}} = 0 \quad (5)$$

results in  $K(L+1)$  simultaneous linear algebraic equations with  $K(L+1)$  unknowns. Their solution may be obtained by a variety of techniques, however the quadratic form of equation (4) enables the optimal set of  $\alpha_{p\ell}$  to be conveniently obtained by an iterative procedure. It was shown in the final technical report of the previous contract (NAS 1-3485) that the iterative procedure is convergent and yields the optimal set of  $\alpha_{p\ell}$  which are then used to compute the time-varying gains.

### The Interpolation Functions

The set of interpolation functions  $\beta_m(t)$  are the means of constraining the solution for the time-varying parameters of the model. It can be shown<sup>1</sup> that if the time-varying gains are unconstrained, the solution for minimum error is trivial. Previous experimental investigation has also shown that a weighted set of staggered triangular time functions with a base length of ten seconds will satisfy the requirements for a meaningful constraint. These triangular functions are given by

$$\beta_m(t) \equiv \begin{cases} 1 - |(t - m\frac{T}{L})| \frac{L}{T} ; & (m-1)\frac{T}{L} \leq t \leq (m+1)\frac{T}{L} \\ 0 ; & \text{elsewhere} \end{cases} \quad (6)$$

where  $T = 60$  seconds, the length of the record and the interval of integration of the performance measure.

and  $L = 5$  seconds.

The integer,  $L$ , determines the base length  $2L$  of the triangular time functions which overlap each other by  $L$  seconds, and directly fixes the allowed time-variability of the gain parameters  $a_i(t)$ . Decreasing the integer,  $L$ , has the effect of allowing greater time-variability in the gains, and reducing the integral squared error which is a measure of the characterization error. Greater time-variability however, leads to increased uncertainty in characterization. The selection of the value of 5 for the integer  $L$ , represents a reasonable compromise that allows the exhibition of time-variations while not permitting such rapid variation as to yield meaningless data. It was decided that a larger value of  $L$  would remove the type of time-variation which was to be studied while a smaller value would introduce excessive variability.

### Presentation of Transfer Characteristics

One method of visually presenting linear transfer characteristics is by means of a graph of the impulse response versus time. However, representing the time-varying transfer characteristics of the human operator by means of step responses has distinct advantages. It allows variations in the control situation to be more readily assessed by the analyst in terms of such

measures as percentage overshoot, delay time, and steady-state gain, which are more easily related to the reactions of human operators. For the case in which the transfer characteristics are time-varying, a second time dimension must be shown which necessitates an isometric type of visual presentation. The information content of the isometric presentation is considerably greater than that of the simple two-dimensional graph.

The special time-varying step response developed for the visual presentation is given by

$$s(t, \tau) \equiv \int_{-\infty}^{\tau} h(t, \lambda) d\lambda \quad (7)$$

where  $h(t, \lambda)$  is the time-varying impulse response defined as the response at time  $t$  to a unit impulse applied  $\lambda$  seconds earlier than  $t$ . The two-dimensional transfer characteristic of (10) is obtained as follows. The output of the network configuration of Figure 1, for any time  $t$ , may be expressed as

$$z(t) = \sum_{i=1}^K \alpha_i(t) g_i(t) \quad (8)$$

where  $g_i(t)$  is the output of the  $i^{th}$  component filter and  $\alpha_i(t)$  is its corresponding gain. The  $\alpha_i(t)$  were obtained by minimizing equation (4) subject to the proper constraints. If  $h_i(\tau)$  designates the impulse response of the  $i^{th}$  component filter then the output  $z(t)$  may be related to the input  $x(t)$  by

$$z(t) = \sum_{i=1}^K \alpha_i(t) \int_{-\infty}^t h_i(\tau) x(t-\tau) d\tau \quad (9)$$

or equivalently,

$$z(t) = \int_{-\infty}^t \left[ \sum_{i=1}^K \alpha_i(t) h_i(\tau) \right] x(t-\tau) d\tau \quad (10)$$

This integral represents the convolution of the input with the network impulse response which can be recognized as the quantity in brackets. The network impulse response which has two independent variables is therefore defined as

$$h(t, \tau) \equiv \sum_{i=1}^K \alpha_i(t) h_i(\tau) \quad (11)$$

The special step response previously defined is obtained by substituting equation (11) into equation (7)

$$s(t, \tau) = \int_{-\infty}^t \sum_{i=1}^K \alpha_i(t) h_i(\tau) d\tau \quad (12)$$

or equivalently,

$$s(t, \tau) = \sum_{i=1}^K \alpha_i(t) \int_{-\infty}^t h_i(\tau) d\tau \quad (13)$$

The actual plotting of the special step responses of the linear models presented in this report was performed by the digital computer by means of special off-line digital plotting equipment.

Because of the higher dimensionality required to adequately display the transfer characteristics of nonlinear time-varying networks they are not presented and comparison with the linear models must be made through the N.I.S.E. defined below, and by inspection of the model outputs.

## Evaluation of Models of the Human Operator

At this point it is useful to define a figure of merit, a metric, by which various models of the human operator may be evaluated. A requirement of this metric is that it accurately assess the fidelity with which the dynamics of the human operator have been characterized. In addition, it must be a readily identifiable quantity. The metric used in this report is defined as

$$\% \text{ N. I. S. E.} = \frac{100 \int_0^T [y(t) - z(t)]^2 dt}{\int_0^T y^2(t) dt} \quad (14)$$

where  $y(t)$  is the output of the human operator and  $z(t)$  is the output of the model. This metric is identified as the normalized integral of the squared error because of the division by the integral of the squared output of the human operator and it is expressed as a percentage.

The normalized integral of the squared error is directly related to the metric  $\rho_a^2$  used by McRuer, Graham, Krendel, and Reisner<sup>6</sup>, Elkind<sup>7</sup>, and others<sup>8,9</sup> in discussions of the ratio of coherent output to the total output of the human operator.  $\rho_a^2$  is usually defined as

$$\rho_a^2 = 1 - \frac{\overline{e^2}}{\overline{y^2}} \quad (15)$$

which is equal to

$$\rho_a^2 = 1 - \frac{\frac{1}{T} \int_0^T [y(t) - z(t)]^2 dt}{\frac{1}{T} \int_0^T y^2(t) dt} \quad (16)$$

The relation then between N.I.S.E. and  $\rho_a^2$  is simply

$$\% \text{ N. I. S. E} = 100 (1 - \rho_a^2) \quad (17)$$

The essential difference between these two performance measures is that one (N.I.S.E.) assesses the amount of incoherent power in the output of the human operator while the other ( $\rho_a^2$ ) assesses the coherent part of the output.

### Description of the Linear and Nonlinear Models

Both types of models used for characterization of the human operator may be described as fixed form filters with time-varying gains. With the exception of the gain parameters, the deterministic characterization theory is not restrictive of the actual components of the filter. A particular model is described as linear or nonlinear depending on whether the filter components contain linear or nonlinear elements.

The components of the linear models may be described as a set of seven Kautz filters. These filters, which are followed by time-varying gains, are described in transform as

$$H_i(j\omega) = \frac{K_i (j\omega - s_1)(j\omega - s_2) \cdots (j\omega - s_{i-1})}{(j\omega + s_1)(j\omega + s_2) \cdots (j\omega + s_{i-1})(j\omega + s_i)} \quad (18)$$

These filters need not be orthonormal, however the filter gains  $K_i$  must be constant. The poles  $s_1, s_2, \dots, s_K$  were chosen so as to fall within (and bracket) the region of the frequency axis in which the poles of the human operator are believed to lie. Preliminary studies indicated that the seven logarithmically spaced poles which were set at 0.75, 1.24, 2.04, 3.37, 5.56, 9.17, and 15.1 radians, would accurately characterize the human

operator in a compensatory tracking system. Because of the inherent capability of the model to assume different characteristics by the optimal adjustment of the gain parameters, the characterization error (N.I.S.E.) is not greatly sensitive to the actual locations of the individual filter poles, provided they are well spaced.

The nonlinear models used in this study were composed of fifteen individual nonlinear filter components followed by time-varying gains. Nonlinear operations, wherein the output is related to the input by a power law comprise the most general class of filters which do not exhibit discontinuities. Consequently the model consisted of the 1st, 3rd, and 5th power of the outputs of a set of 5 linear Kautz filters all multiplied by an appropriate time-varying gain which was computed as in the linear case. The poles of these Kautz filters were logarithmically spaced at 1.50, 2.38, 3.77, 5.97, and 9.47 radians. There were therefore, a total of 15 time-varying parameters in the nonlinear model which, in combination with the nonlinear elements, made it possible to characterize a wide range of nonlinearities on a time-varying basis. The complexity of the digital program and the amount of storage required for such a large number of time-varying parameters prevented the consideration of more than 5 Kautz filters. More advanced techniques could no doubt be used to expand the program to 7 or more Kautz filters, however the increased costs would hardly justify a reduction in the small characterization error that can be achieved with 5 Kautz filters and 15 time-varying parameters.

### Digital Application of the Deterministic Characterization Theory

Effecting the solution for the time-varying gains of the optimal filter that minimizes the error between the output of the filter and that of the human



operator requires the solution of a large number of simultaneous linear algebraic equations. The generation of their coefficients and the computation of the filter transfer characteristics requires an extensive amount of computation and storage. Modern high-speed digital computers capable of being programmed in the scientific FORTRAN language are ideally suited for performing the required calculations. With the recent development of digital plotting equipment it has been advantageous to program the computer to actually plot the desired time-varying step responses of the optimal filter in isometric. This added convenience has facilitated comparison of different models and has resulted in great economy of time and resources.

The digital computer program used in this study to compute the time-varying transfer characteristics of the human operator is the result of further development and updating of the digital computer program used in the previous study.\* Extensive changes were required to increase the computational efficiency, optimize the data storage by taking advantage of certain symmetries of the interpolation functions, and incorporate the automatic plotting of the isometric presentation. Experience has shown that it is more economical to tailor digital programs to the specific task than to compile digital programs for broad application as these latter have a tendency to become highly inefficient.

---

\* NASA Contract No. NAS 1-3485

The essential steps of the digital computation are the following:

1. Read into storage the input record and output record of the human operator and also other parameters for the run such as the filter coefficients, data sampling rate, etc.
2. The input record is filtered by digital filters which represent the chosen set of fixed component filters, thus producing an array of numbers representing the sampled waveforms  $g_i(t)$ .
3. The coefficients of the set of linear algebraic equations are computed by numerical integration techniques.
4. The linear algebraic equations are solved for the set of weights  $\alpha_{p\ell}$  by an iteration technique.
5. These weights are then used to compute the time-varying gains  $a_i(t)$  from Equation (3).
6. The unit step responses  $S_i(\tau)$  of the fixed component filters are then calculated by numerical filtering techniques. To obtain the step response of the optimal filter at any time  $t_0$  the step responses  $S_i(\tau)$  are multiplied by the gains  $a_i(t_0)$  and summed as in Equation (13). This procedure is followed for other times  $t_1, t_2, \dots$  until the step responses have been obtained for about 15 equally spaced intervals of the time  $t$  between  $t = 0$  and  $t = T$ .
7. These step responses are then plotted by the computer in isometric form as in Figures 6 through 25.

A number of special digital techniques extensively developed at CAL were utilized in programming the deterministic characterization theory for digital computation of the time-varying transfer characteristics. One of these, the Tustin method<sup>10</sup> in particular, is extremely useful for simulating the response of continuous-time networks such as filters on the digital computer. The Tustin method is essentially a method for the approximation of continuous-time control systems by means of discrete-time equations. Its use is restricted to the simulation of linear, time-invariant systems such as the Kautz filter components described previously, that can be described by transfer functions. This method was used to accurately determine the filter outputs at the sampling times so that the trapezoidal rule of numerical integration could be used in computing the coefficients of the linear algebraic equations from the filter outputs. The Tustin method was also used to obtain the step responses  $S_i(\tau)$  of the Kautz filter components which were then used to compute the time-varying step responses  $S(t, \tau)$  of the linear models as shown in Figures 6 through 25.

The basic sampling rate at which the tracking data was sampled for analysis by the computer was doubled from that used in the previous study. It was believed that sampling the tracking signals at a rate of 20 samples per second would increase the accuracy of characterization by reducing the errors inherent in the trapezoidal approximation to integration in the computation of the coefficients of the linear equations.

### III. DESIGN OF THE EXPERIMENTAL FACILITY

The particular objective pursued in the design and construction of the experimental tracking facility was the capability for generating significant and reliable human operator tracking data. Minimum complexity consistent with the stated objective was an important consideration in the design of the apparatus.

To facilitate the comparison of the results of this investigation with previous results and with those obtained by personnel of the NASA Langley Research Center, the system block diagram shown in Figure 2 was chosen as the basis for the design of the equipment. The experimental facility is composed of the following major components:

- a. Input signal generators
- b. Signal processor
- c. Display console
- d. Hand controller
- e. Controlled dynamics
- f. Data recorder

These components will be individually described in subsequent paragraphs.

The power spectrum of the input signal and the form of the controlled element follow-up dynamics are identical to those used by the NASA Langley Research Center to generate the two-axis tracking signals which were analyzed by CAL on Contract NAS 1-3485.

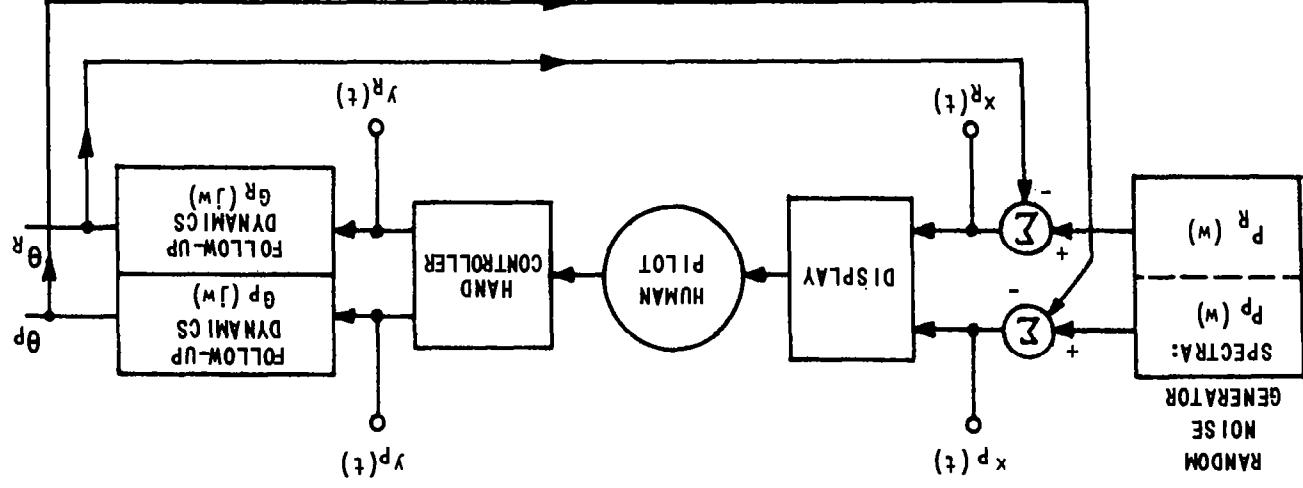


Figure 2 SYSTEM BLOCK DIAGRAM USED TO GENERATE CONTINUOUS TWO-AXIS TRACKING DATA

## Input Signals

The independent and uncorrelated input signals for each axis were obtained by appropriate low-pass filtering of the output of wide-band random noise generators. These signals were recorded on separate channels of a Precision Instrument FM tape recorder. The power spectrum of the input signals for each axis can be expressed as

$$P(\omega) = \frac{K_p^2}{(1 + (\omega/.25)^2)^2} \quad (19)$$

A separate recording of random noise signals with identical statistics was used by the various pilots for practicing. In this way, some control was exercised over the amount of learning experienced by each pilot. Similarly, the use of the same random signals for each run allowed direct comparison of their responses. Learning or memorization of the input signals despite their repeated use, can be considered to be negligible because of the nature of compensatory tracking in which the input signals are not displayed directly, and because the time length of the signals was sufficiently long so as to avoid memorization.

## Signal Processor

Signal processing as well as the controlled dynamics, were simulated on CAL's Electronics Associates TR-48 general purpose analog computer. Also programmed on the analog computer were the active compensation networks for the d'Arsonval panel meters used in the display, and the circuitry to simulate the artificial-horizon display familiar to most aircraft pilots.

Provisions were made for switching the appropriate displays when necessary as well as for monitoring the various system signals during tracking. When a particular display was not being used, it was blocked from view by means of a panel insert.

Compensation for the panel meters used in the display was deemed necessary because of their marked deficiencies in frequency response. Typical response, for a high quality meter such as the Simpson #1327C meter decreases at the rate of 40 db per decade above about 1 cycle per second. It was therefore essential that some form of frequency compensation be employed to augment the gain at all frequencies where the human operator can respond. The frequency response of the meters, obtained by direct measurement, is shown in Figure 3. An active compensating network to be placed in series with the meter was synthesized and programmed on the analog computer. This network is given in transform by

$$F(j\omega) = K_F \frac{\left(\frac{j\omega}{3\pi}\right)^2 + \frac{\sqrt{2}}{3\pi} j\omega + 1}{\left(\frac{j\omega}{100}\right)^2 + \frac{\sqrt{2}}{100} j\omega + 1} \quad (20)$$

The frequency response of the compensated meter, shown in Figure 4, was extended to beyond 5 cycles per second which is well beyond the response capability of humans. For the purposes of the experiment therefore, the transfer function of the augmented display meters can be considered unity in the range of frequencies contained in the displayed signals. It was important to ensure a unity transfer function for the display so that display dynamics would not be reflected in the measured characteristics of the pilot.

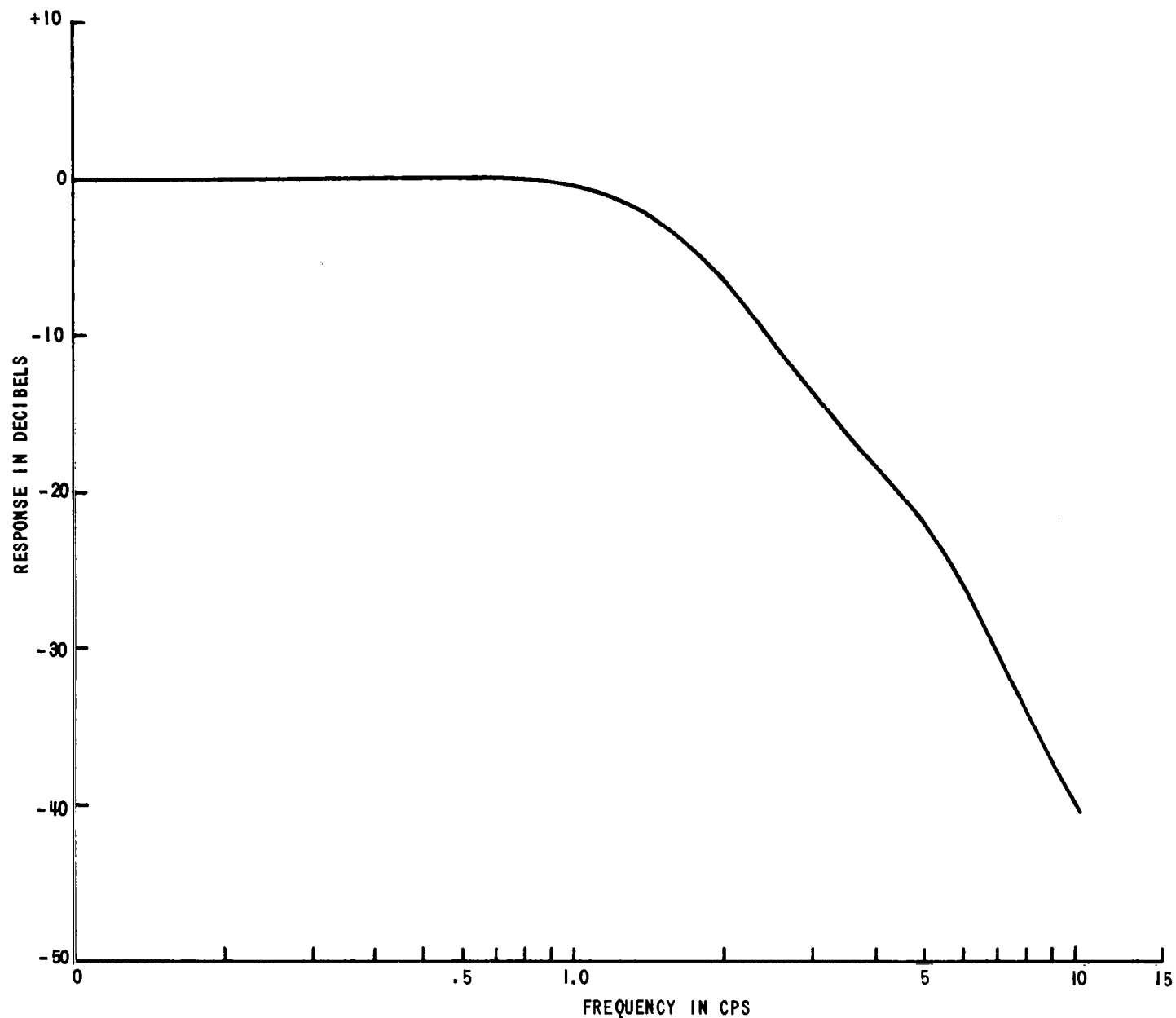


Figure 3 FREQUENCY RESPONSE - SIMPSON #1327C METER



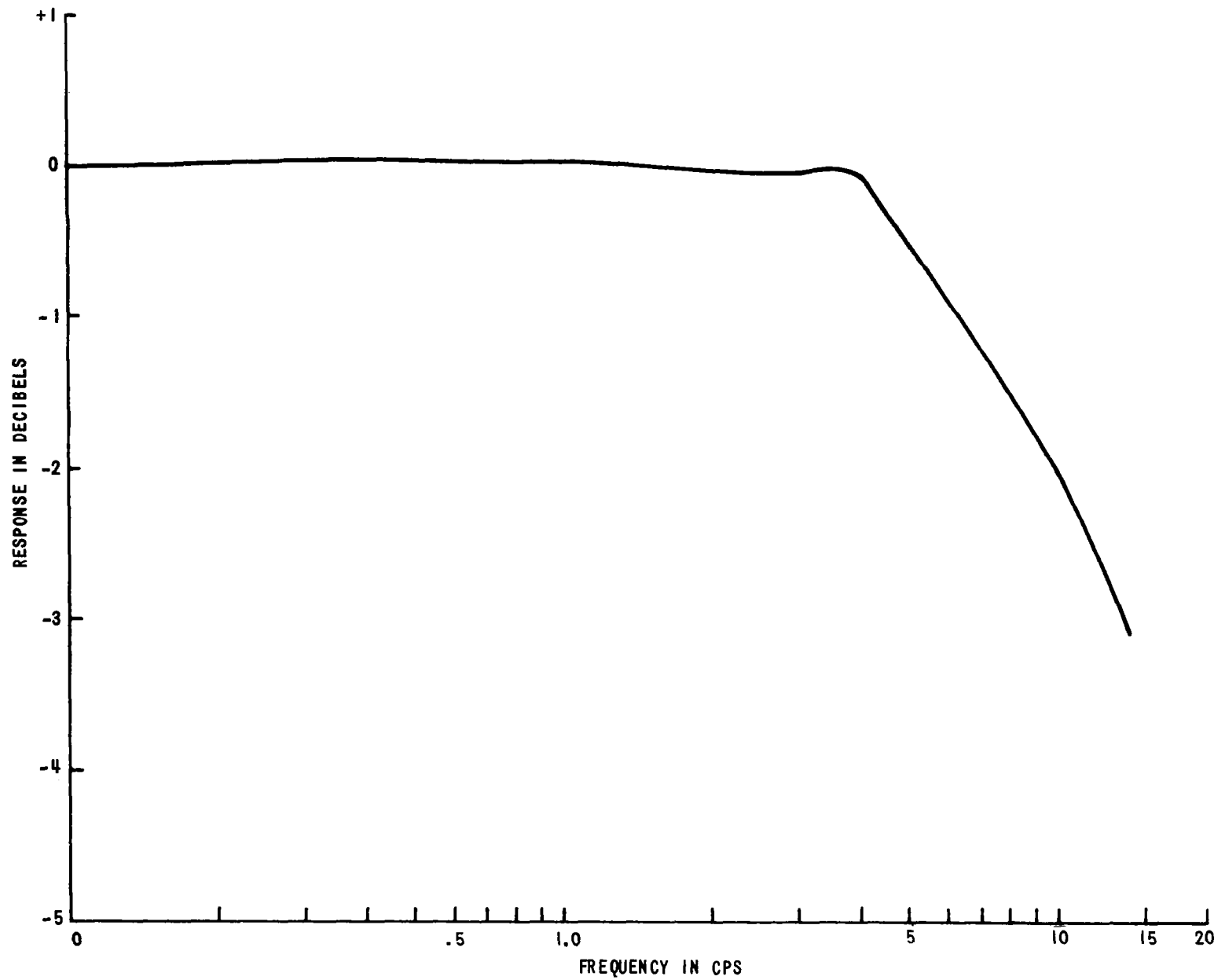


Figure 4 FREQUENCY RESPONSE - SIMPSON #1327C METER WITH ACTIVE COMPENSATION NETWORK

## Display Console

The various display instruments which make up the console were mounted on a standard six foot relay rack. A 5" oscilloscope, centrally mounted at eye-level, was used as the display instrument for Tasks 0, 1, and 2. For Task 0 and 1, a transparent screen with vertical and horizontal centimeter ruled markings covers the face of the oscilloscope. Tracking errors representing the difference between the random input signal and the output of the follow-up dynamics are displayed by the proportional displacement of a dot from the clearly marked center of the oscilloscope screen. The artificial horizon of Task 2 was displayed on the oscilloscope behind a transparent screen on which was painted an aircraft symbol to be used as an aid by the pilots in gaining perspective. When the oscilloscope display was not in use, its opening in the display panel was covered by a panel insert.

D'Arsonval panel meters with 3-1/2 inch movements were used to display the appropriate tracking errors in each axis in Tasks 3 and 4. A third panel meter was used to display the workload random signal in Task 4. The workload switch which added the appropriate bias to the meter was conveniently located beside the workload meter in easy reach of the subject.

For purposes of visually monitoring the subject during tracking runs, a 12 x 19 inch section of one-way glass was installed above the oscilloscope display panel. The proper adjustment of illumination levels on each side of the one-way glass permitted the subject to be observed without the observer being detected. This feature was used mainly for the purpose of acquiring data on eye motions during tracking and for evaluation of the preliminary training.

## Hand Controller

The hand controller used for the tracking experiments consisted of a pistol-grip handle approximately 6 inches long to the pivot point. It could be moved in each of 2 axes, a maximum of 45 degrees. Potentiometers attached to the pivot, translated angular deflection in each axis as a proportional voltage in the range  $\pm 10$  volts. Inertia was negligible and the adjustable damping was set to zero. The controller had been fitted with rotational springs that returned the control stick, upon release, to a vertical reference position. The controller and display panel are illustrated in Figure 5.

## Controlled Dynamics

The transfer functions of the follow-up dynamics, for both pitch and roll, which were programmed on the analog computer are given by

$$G(j\omega) = \frac{K_G}{j\omega(j\omega+1)} \quad (21)$$

The controlled dynamics were made identical in each axis to allow cross comparison of the performance of the human operator in each axis.



4 1793PM

Figure 5 EXPERIMENTAL TRACKING FACILITY SHOWING  
HAND-CONTROLLER AND DISPLAY PANEL

## Data Recording and Sampling

The process of recording the input and output signals of the pilot and the subsequent conversion to punched cards was carefully controlled. Systematic errors such as the distortion and drift that normally occur in F.M. tape recording were essentially eliminated by directly recording the signals in analog form on paper with a wide bandwidth, multichannel, high quality recorder. Timing pulses to ensure synchronization of the ensemble data were recorded on a separate channel of the paper recorder. The paper recordings were then sampled, at each timing pulse, at the rate of 20 samples per second with a manually operated Telereader machine which transformed the data into punched card form for processing on the IBM 7044 digital computer. Digital replotting of the punched card data and other checking procedures were used to insure that the data, in digital form was well within  $\pm 0.5$  % tolerance.

#### IV. TIME-VARYING ANALYSIS OF TRACKING DATA

The great bulk of the computation performed on this contract was directed at obtaining linear time-varying models of the human pilot in the tasks described earlier in this report. However, both nonlinear time-varying and nonlinear constant coefficient models were also obtained for a small number of data runs. In this chapter, the results of all time-varying models, both linear and nonlinear, will be presented and discussed. Nonlinear constant coefficient models are discussed in the next chapter.

For the experiments that were performed, a set of 10 individual data runs and a set of 10 ensemble data runs were obtained, half of each set of runs in pitch and the other half in roll. All 20 of these runs were analyzed so as to obtain optimum linear time-varying models. The linear time-varying step responses of the models and corresponding signals are presented in Figures 6 through 25. The caption of each figure designates the particular experiment, axis, and whether the results are for individual or ensemble data. The time-waveforms contained in each plot are the error signal that appears on the display, the human operator's stick output, and the error between the stick output and the time-varying model output. In some of the plots, the model output is also included, as a result of digital program improvements during the analysis. All independent-variable axes have the units of seconds. The gain axis is dimensionless, and the time waveforms in all of the figures are plotted on the same scale of arbitrary amplitude units, perhaps volts or fractions of a radian.

In addition to the plots obtained, the errors in the characterizations are given in concise form in Tables 2 and 3. The measure, % N.I.S.E. as defined in Chapter II, was used to describe the errors between the models and the tracking data.

### Rules by Which the Human Operator Responds

The plots described above were studied in great detail to determine generalities or rules that might explain the operators' responses, particularly in regard to time-variation. Before presenting these rules, it is necessary to caution the reader against forming hasty conclusions or casually attempting to explain the nature of the rules by which operators respond. What appears to be a clear relationship in or one two runs may be totally disproved by other runs, or even by parts of the same run. The rules stated below are believed to be valid for all of the computer runs.

1. All of the computer runs exhibit a nonminimum phase model step response over intervals of time. This characteristic is easily detected by an observer, since a network is nonminimum phase if its step response initially goes negative and also approaches a positive final value. This nonminimum phase characteristic has occurred repeatedly and consistently in both this study and the previous one.\* It is believed to be caused by the reaction time of the human operator, and has in the past been approximated by a pure delay by other investigators.

---

\*Because these nonminimum phase characteristics have not been obtained by other investigators (to the best of our knowledge) tests were performed on the previous contract to assure correctness of this result. The tests performed on that study showed that a minimum phase network is detected by the deterministic theory with minimum phase characteristics, and a non-minimum phase network is detected by the theory with nonminimum phase characteristics.

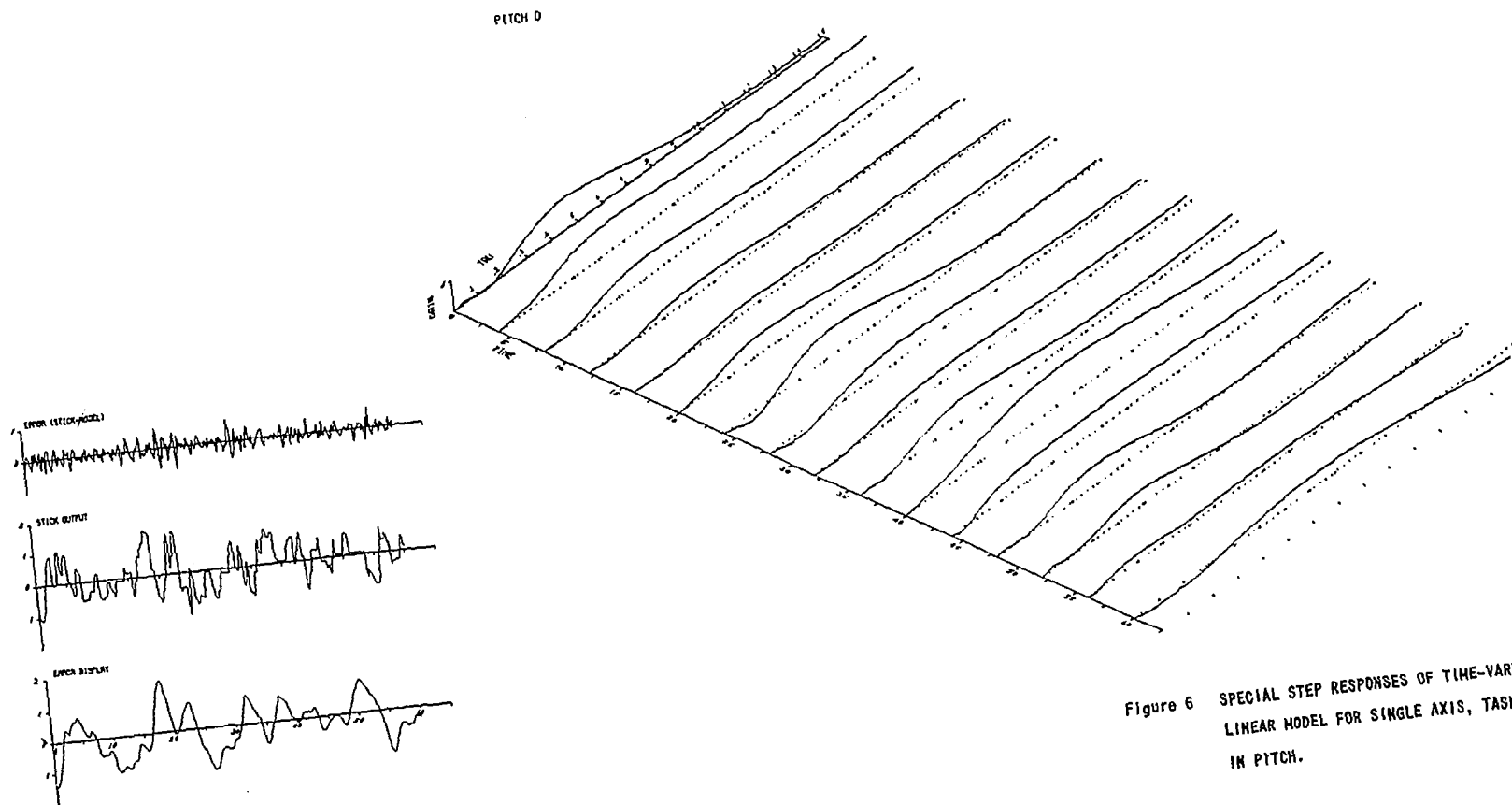
Table 2  
CHARACTERIZATION ERRORS FOR LINEAR TIME-VARYING MODELS  
OF AN INDIVIDUAL PILOT

TASK NO.	DISPLAY	NO. OF AXES	PITCH AXIS		ROLL AXIS	
			% NISE	FIG. NO.	% NISE	FIG. NO.
0	SCOPE	1	9.71	6		
0	SCOPE	1			5.37	11
1	SCOPE	2	8.44	7	4.24	12
2	ART. HORIZ.	2	7.53	8	4.53	13
3	2 METERS	2	14.6	9	5.87	14
4	2 METERS WITH WORKLOAD	2	12.4	10	5.81	15

Table 3  
CHARACTERIZATION ERRORS FOR LINEAR TIME-VARYING  
OF THE ENSEMBLE DATA

TASK NO.	DISPLAY	NO. OF AXES	PITCH AXIS		ROLL AXIS	
			% N.I.S.E.	FIG. NO.	% N.I.S.E.	FIG. NO.
0	SCOPE	1	3.96	16		
0	SCOPE	1			1.90	21
1	SCOPE	2	3.48	17	2.88	22
2	ART. HORIZ.	2	3.48	18	4.60	23
3	2 METERS	2	4.37	19	2.72	24
4	2 METERS WITH WORKLOAD	2	7.69	20	4.40	25





PITCH 1

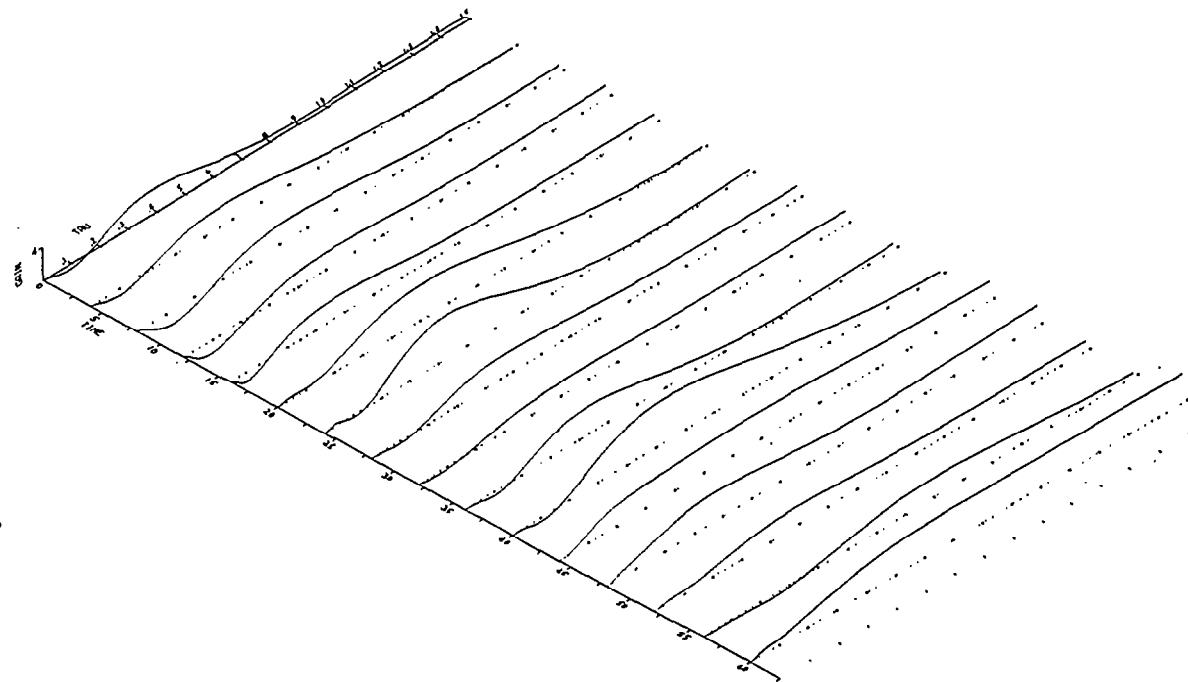
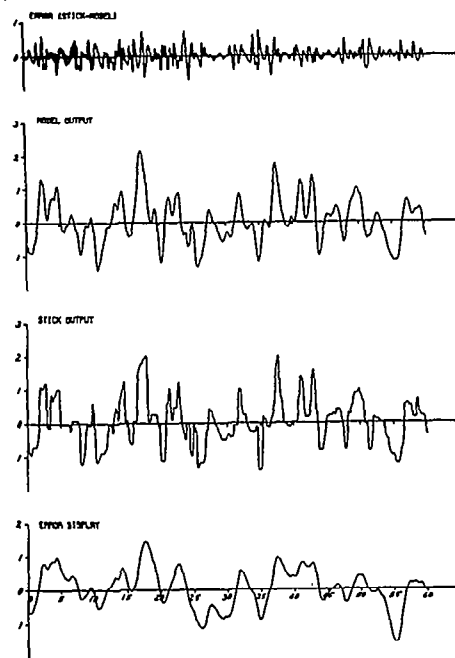


Figure 7 SPECIAL STEP RESPONSES OF TIME-VARYING LINEAR MODEL FOR PITCH AXIS, TASK 1, SPOT DISPLAY.

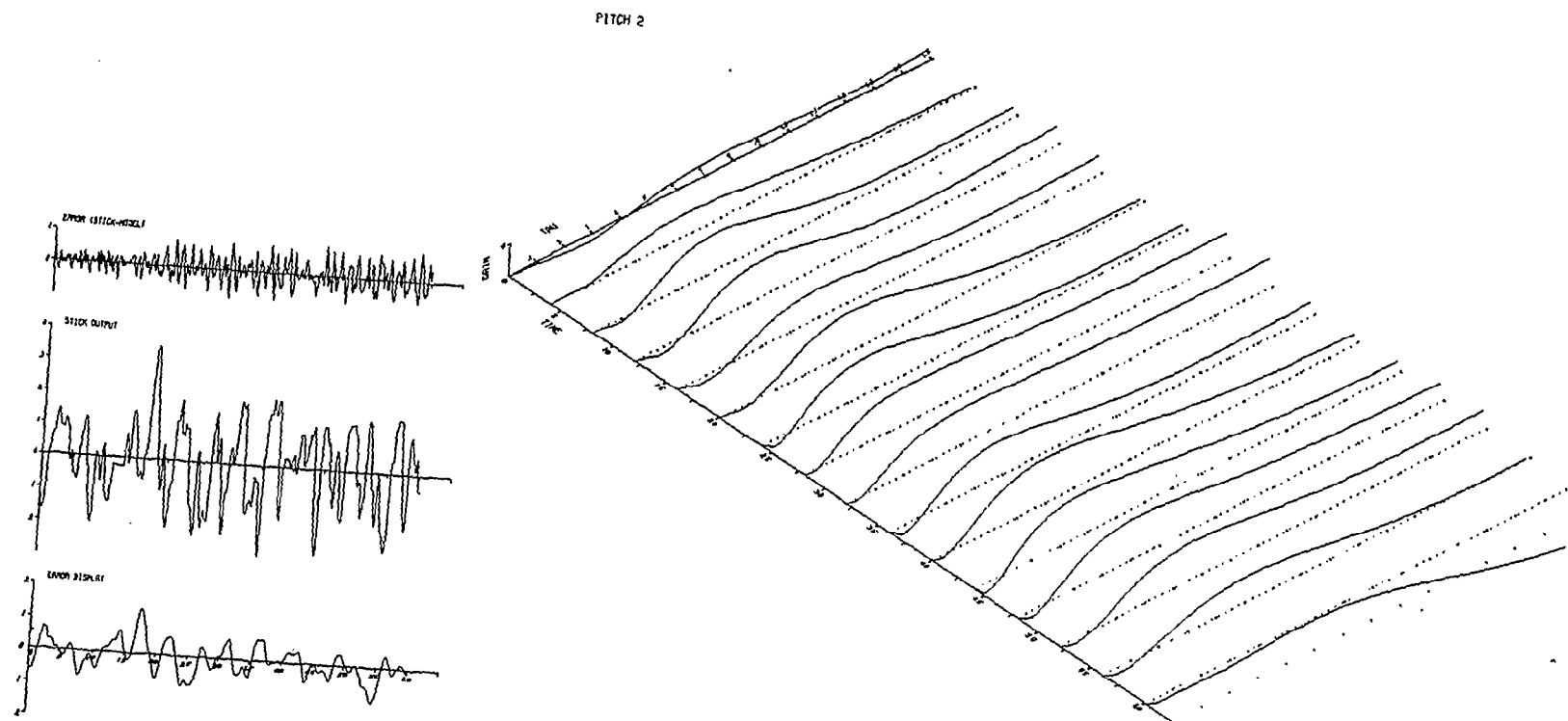


Figure 8 SPECIAL STEP RESPONSES OF TIME-VARYING  
LINEAR MODEL FOR PITCH AXIS, TASK 2,  
ARTIFICIAL HORIZON.

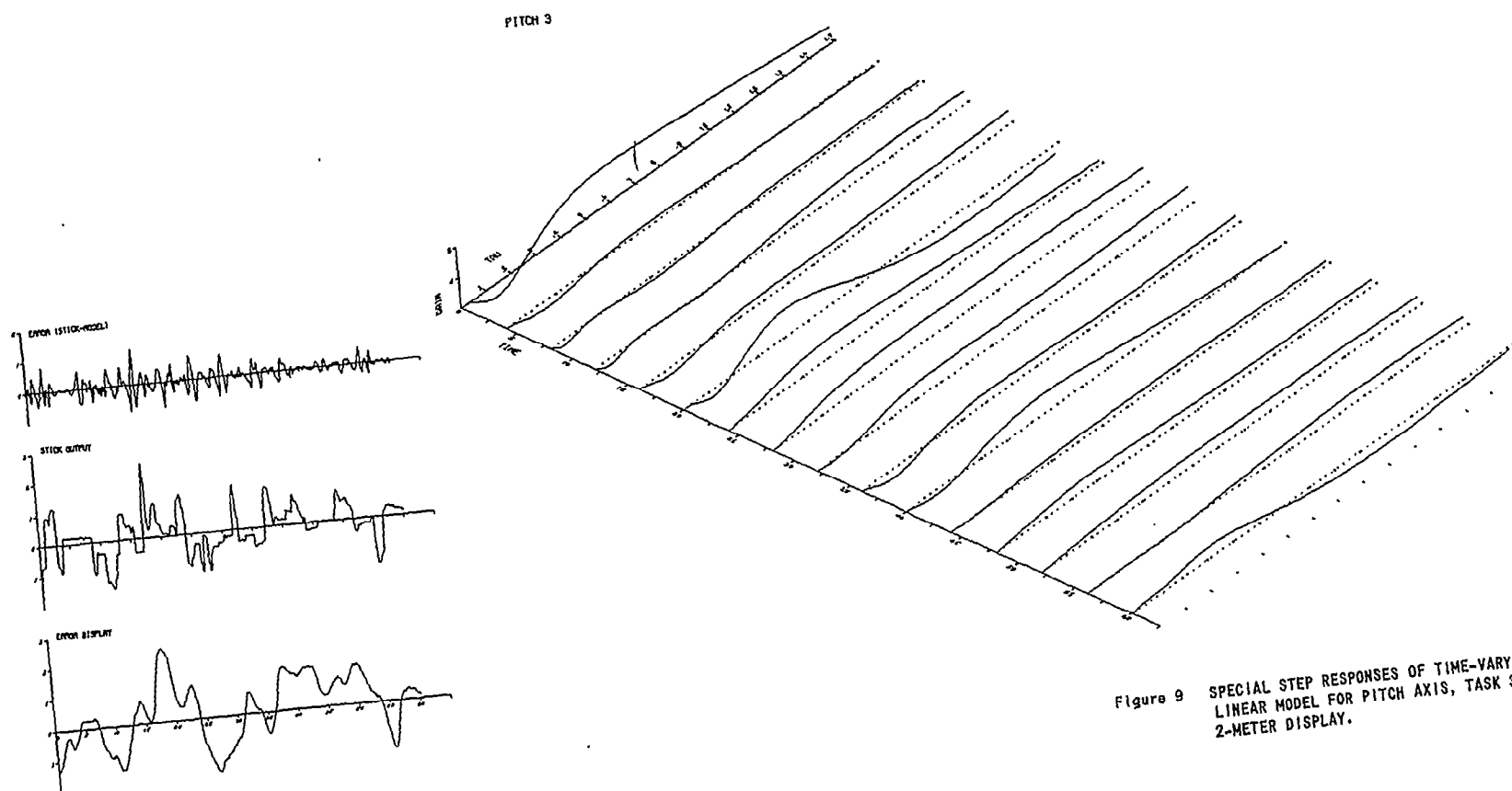
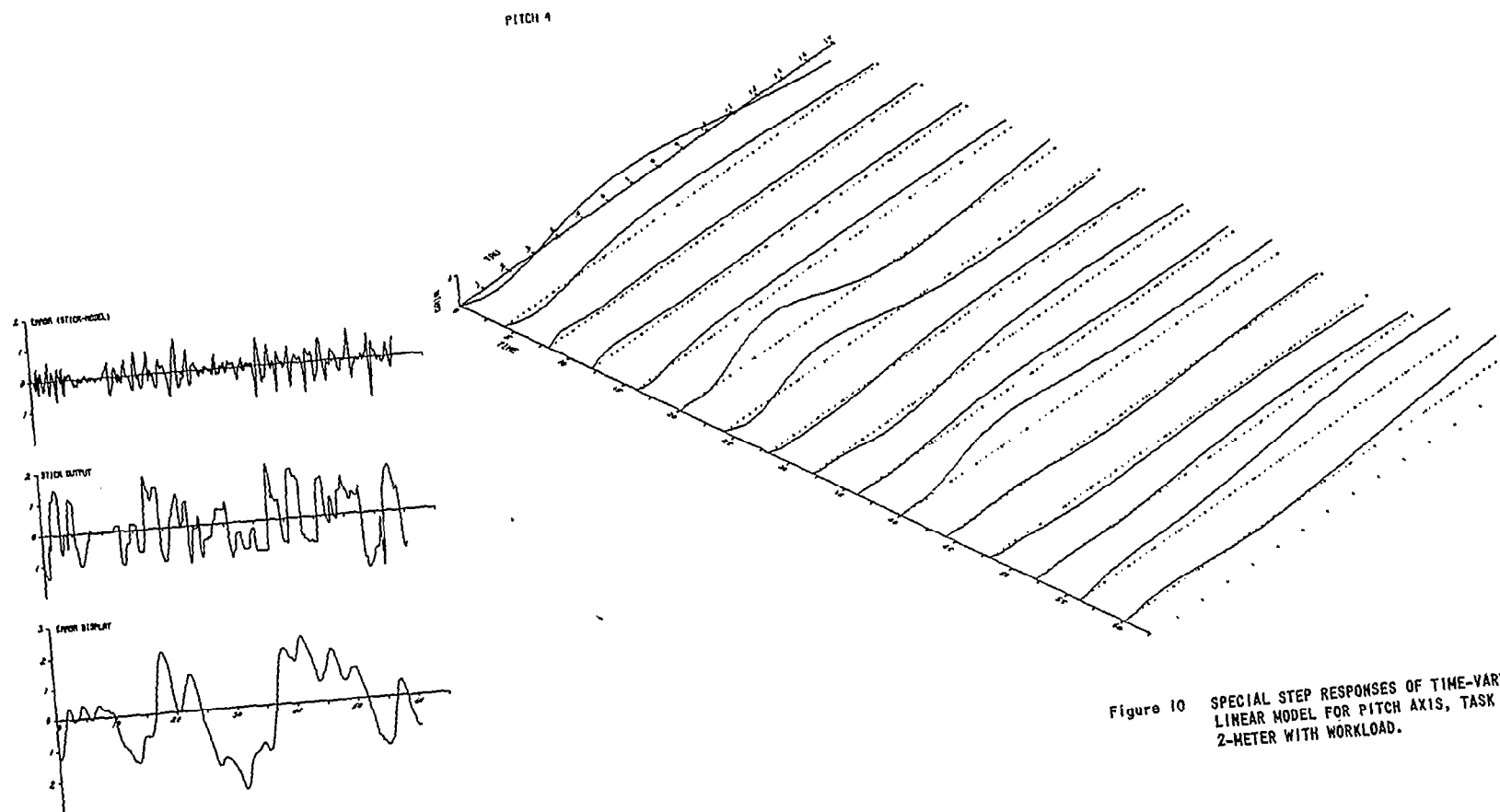


Figure 9 SPECIAL STEP RESPONSES OF TIME-VARYING LINEAR MODEL FOR PITCH AXIS, TASK 3, 2-METER DISPLAY.



ROLL 0

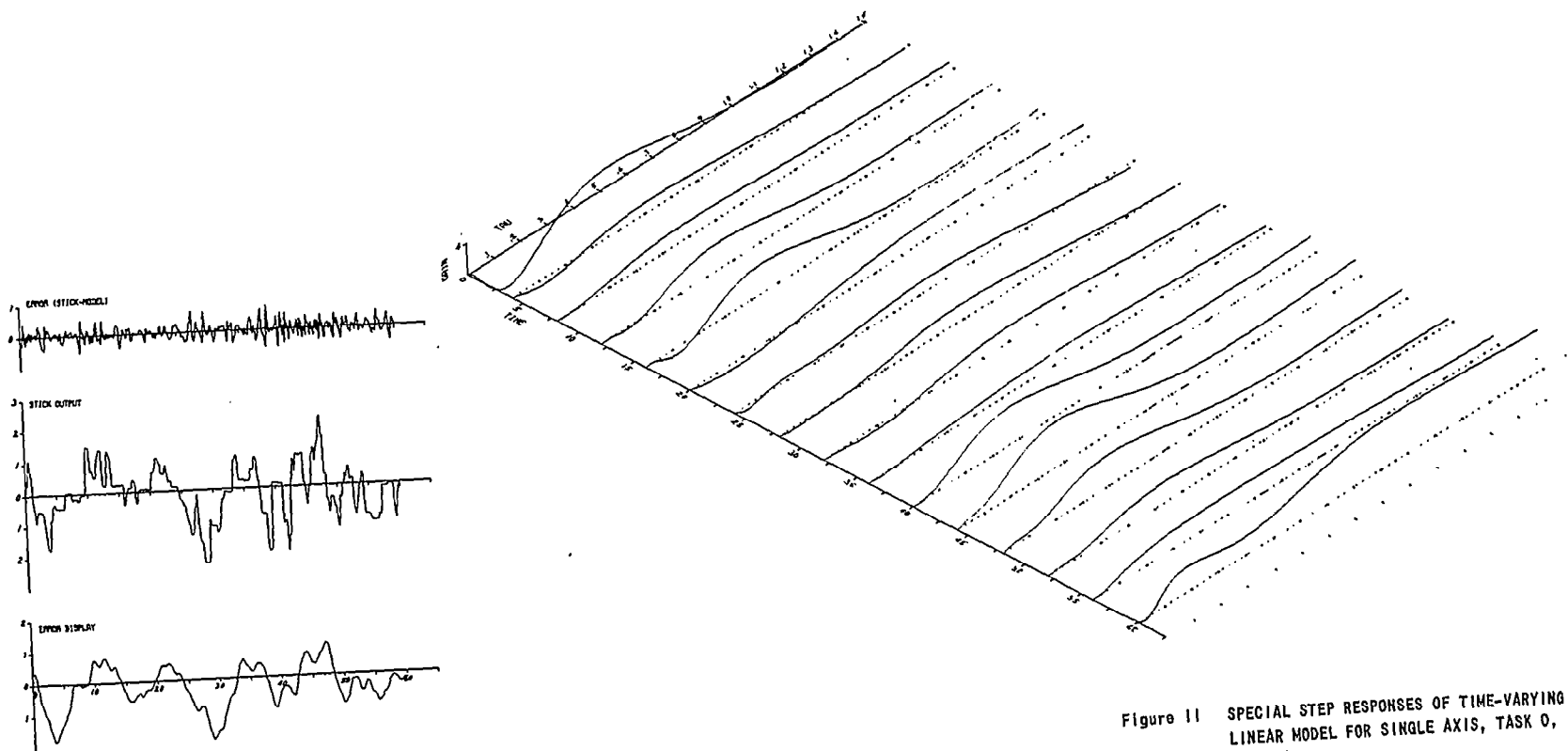


Figure 11 SPECIAL STEP RESPONSES OF TIME-VARYING LINEAR MODEL FOR SINGLE AXIS, TASK 0, IN ROLL.

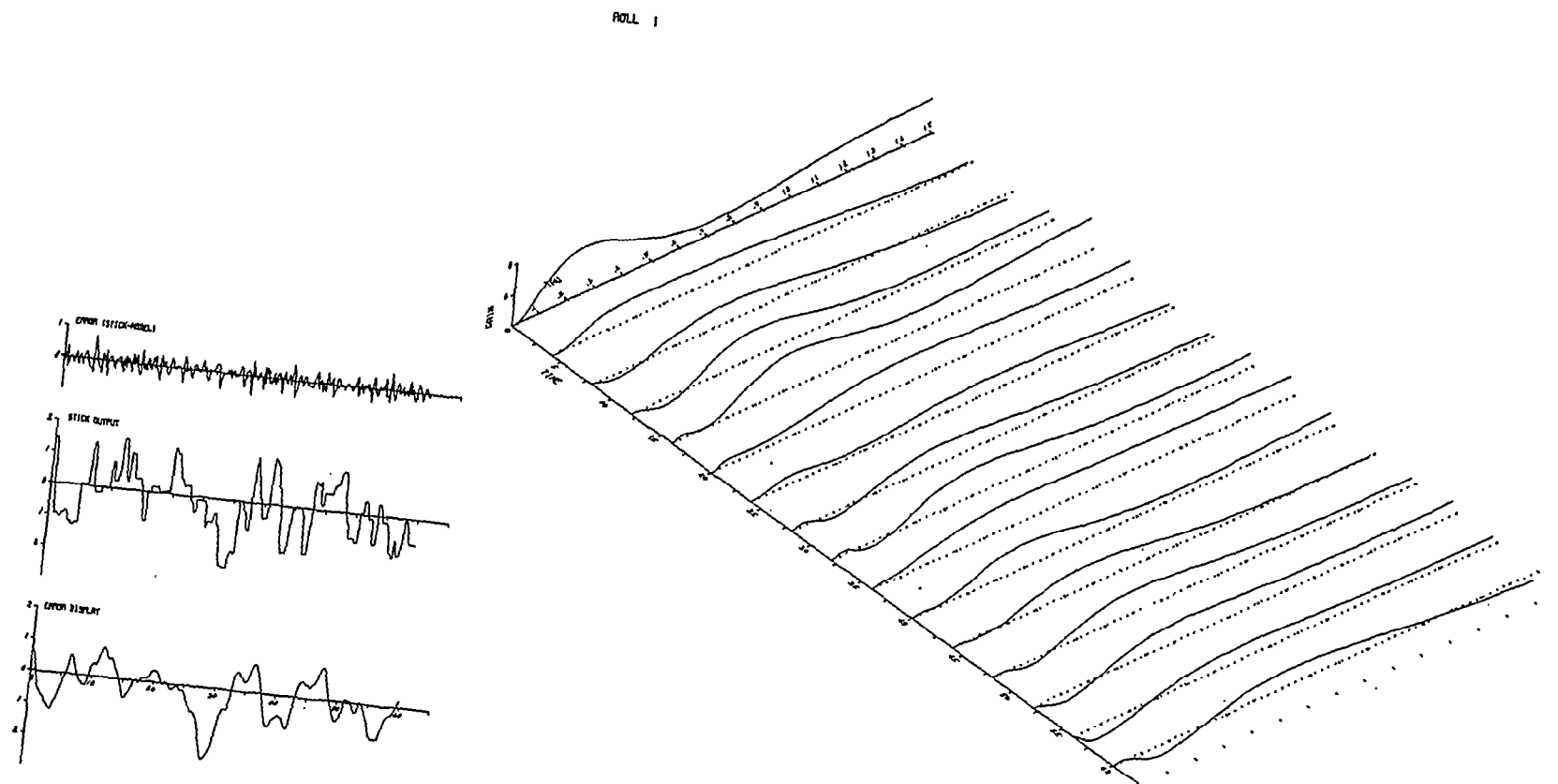


Figure 12 SPECIAL STEP RESPONSES OF TIME-VARYING  
LINEAR MODEL FOR ROLL AXIS, TASK 1,  
SPOT DISPLAY.

ROLL 2

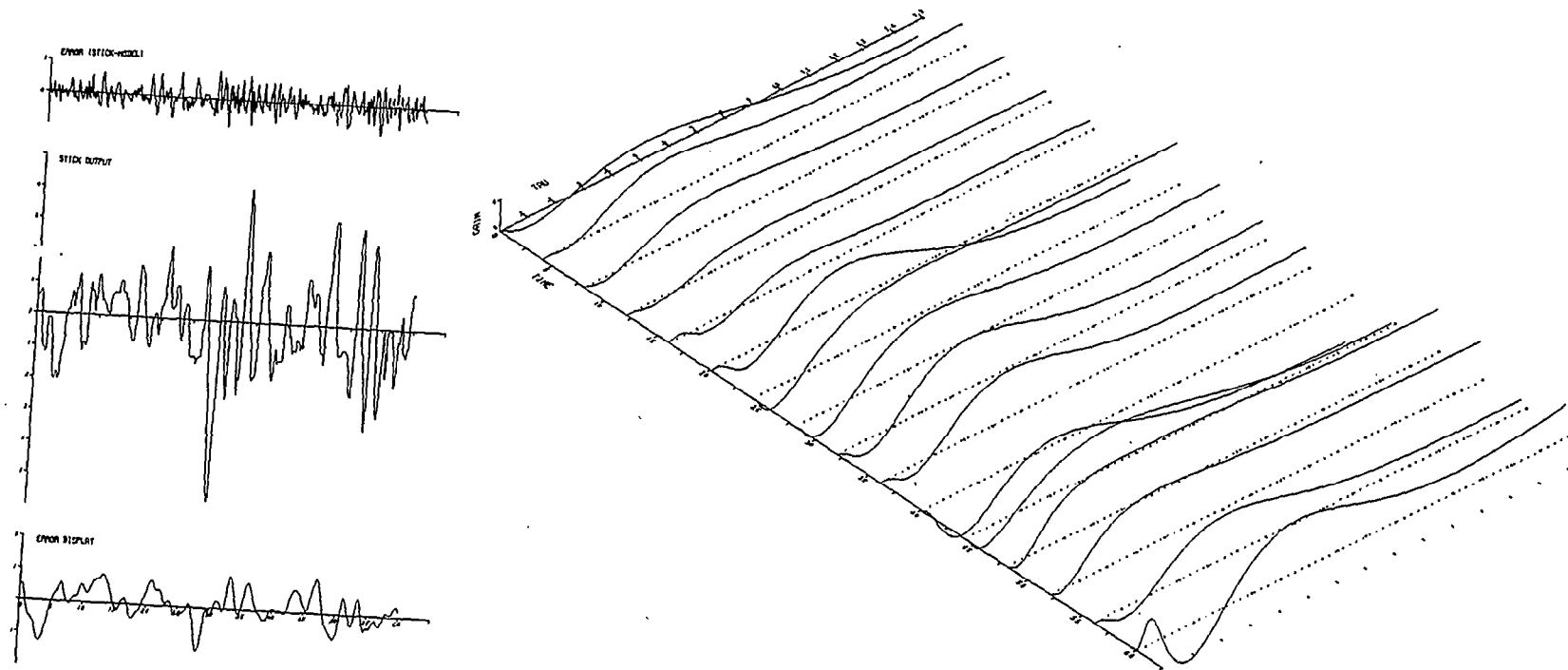
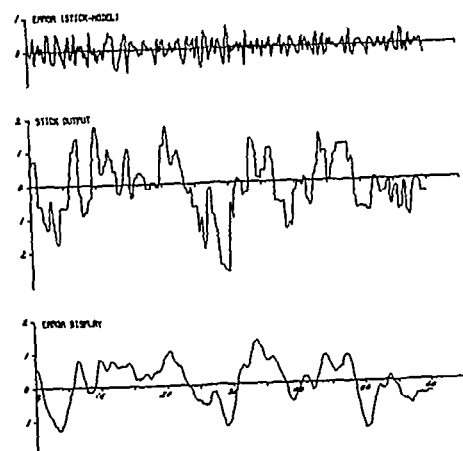


Figure 13 SPECIAL STEP RESPONSES OF TIME-VARYING LINEAR MODEL FOR ROLL AXIS, TASK 2, ARTIFICIAL HORIZON.





ROLL 3

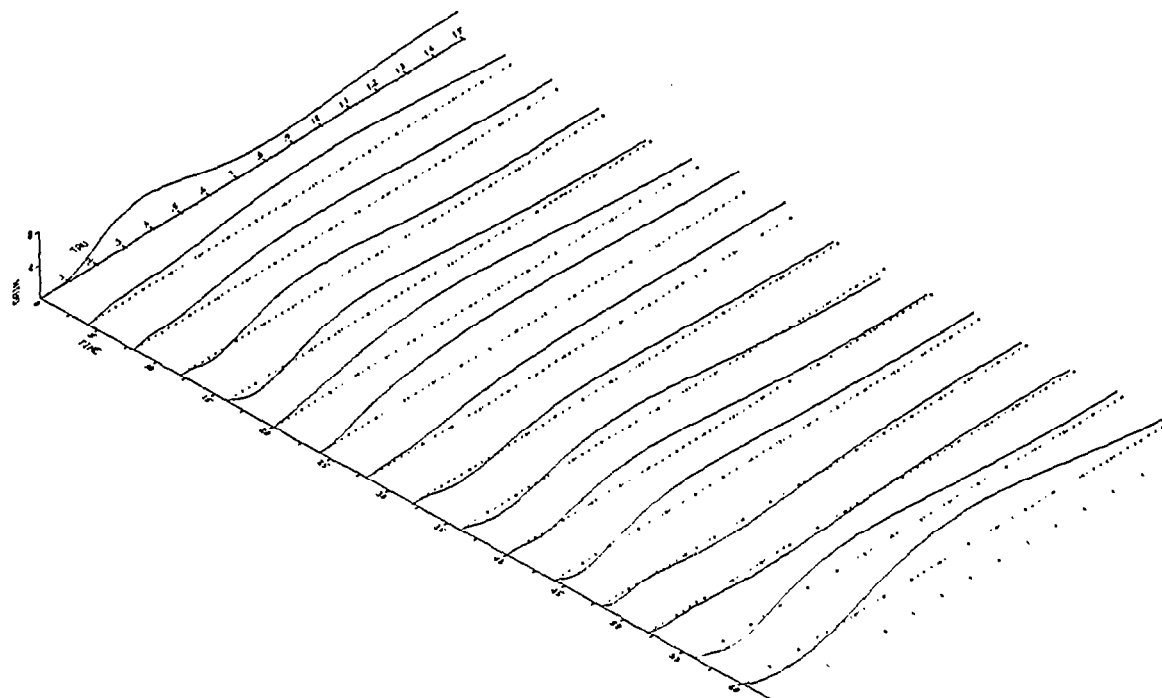


Figure 14 SPECIAL STEP RESPONSES OF TIME-VARYING  
LINEAR MODEL FOR ROLL AXIS, TASK 3,  
2-METER DISPLAY.

ROLL 4

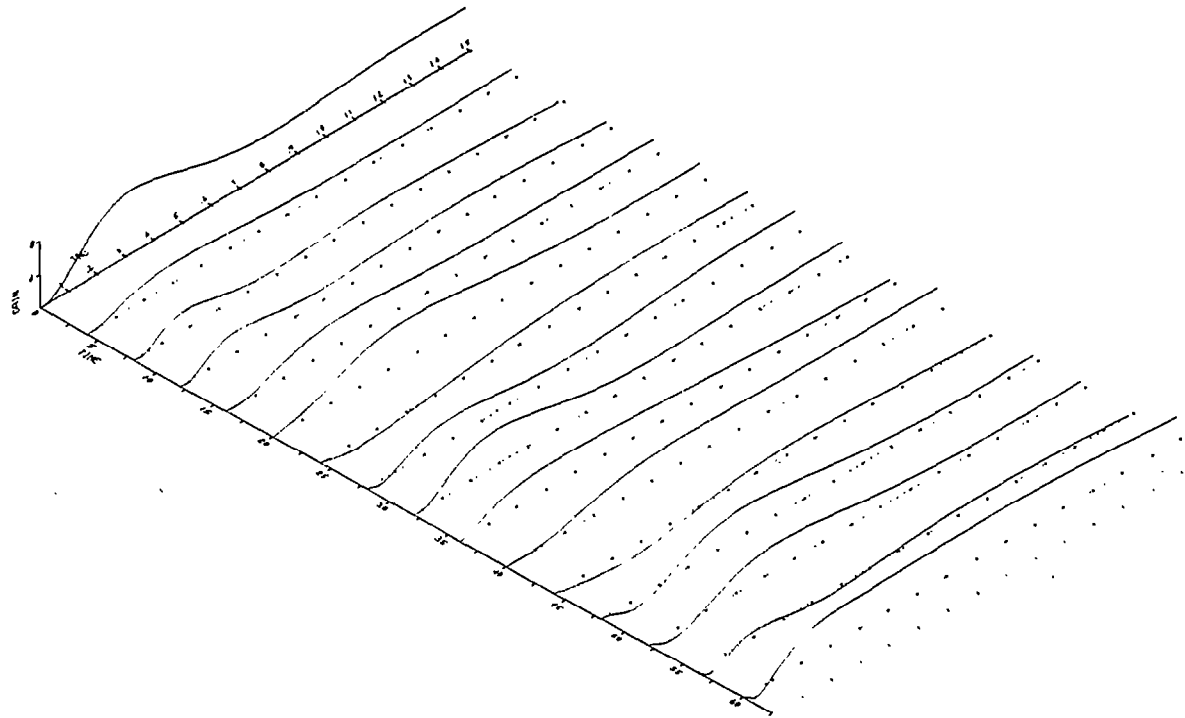
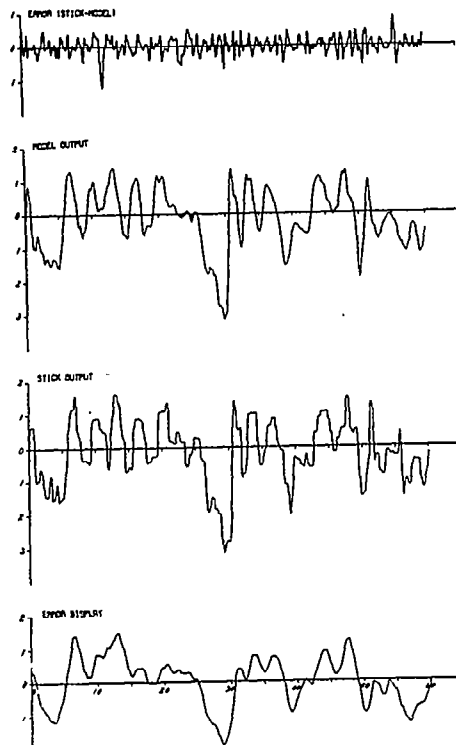


Figure 15 SPECIAL STEP RESPONSES OF TIME-VARYING LINEAR MODEL FOR ROLL AXIS, TASK 4, 2-METER WITH WORKLOAD.

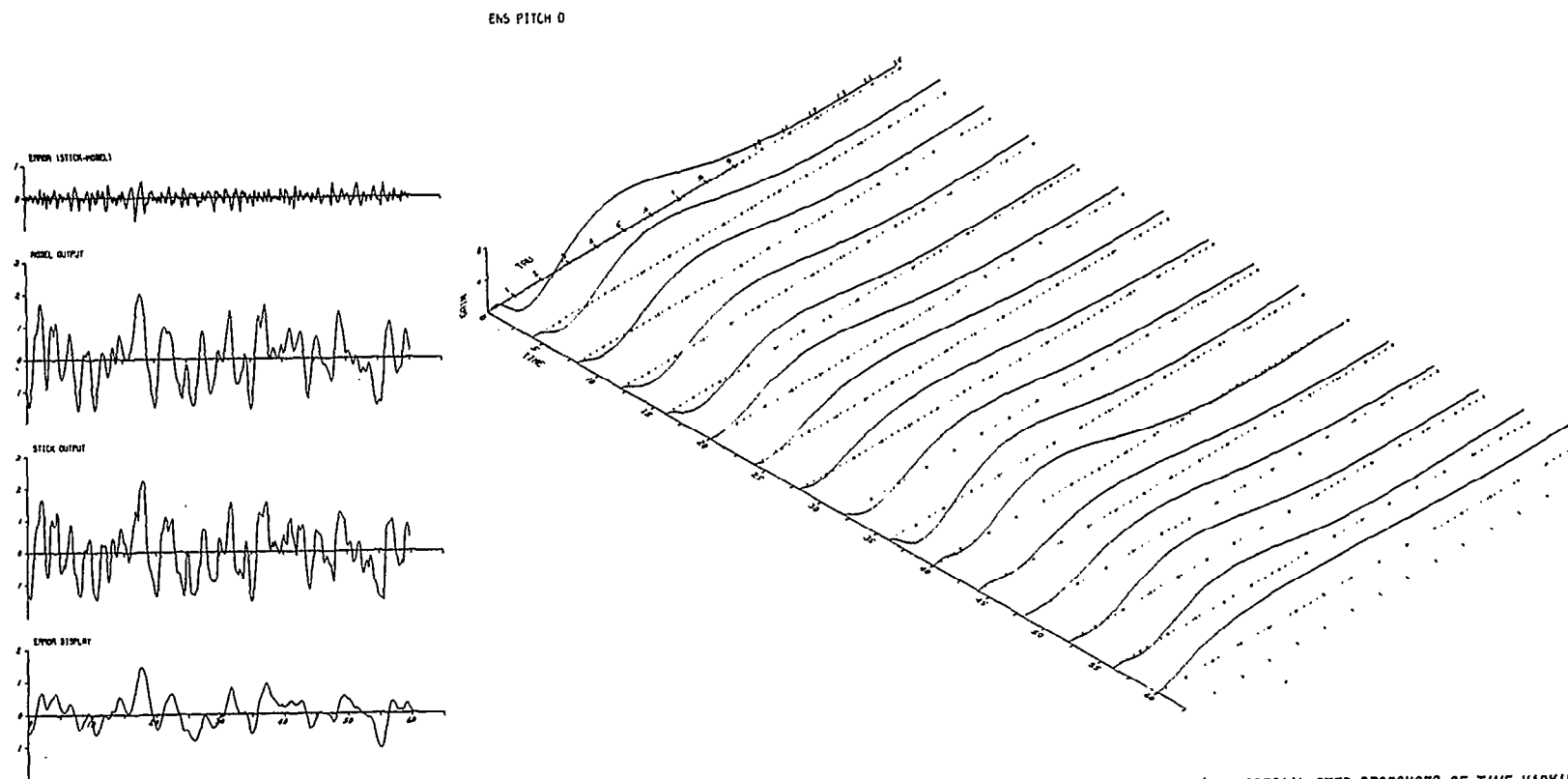


Figure 16 SPECIAL STEP RESPONSES OF TIME-VARYING LINEAR MODEL FOR SINGLE AXIS, TASK 0, IN PITCH, ENSEMBLE DATA.

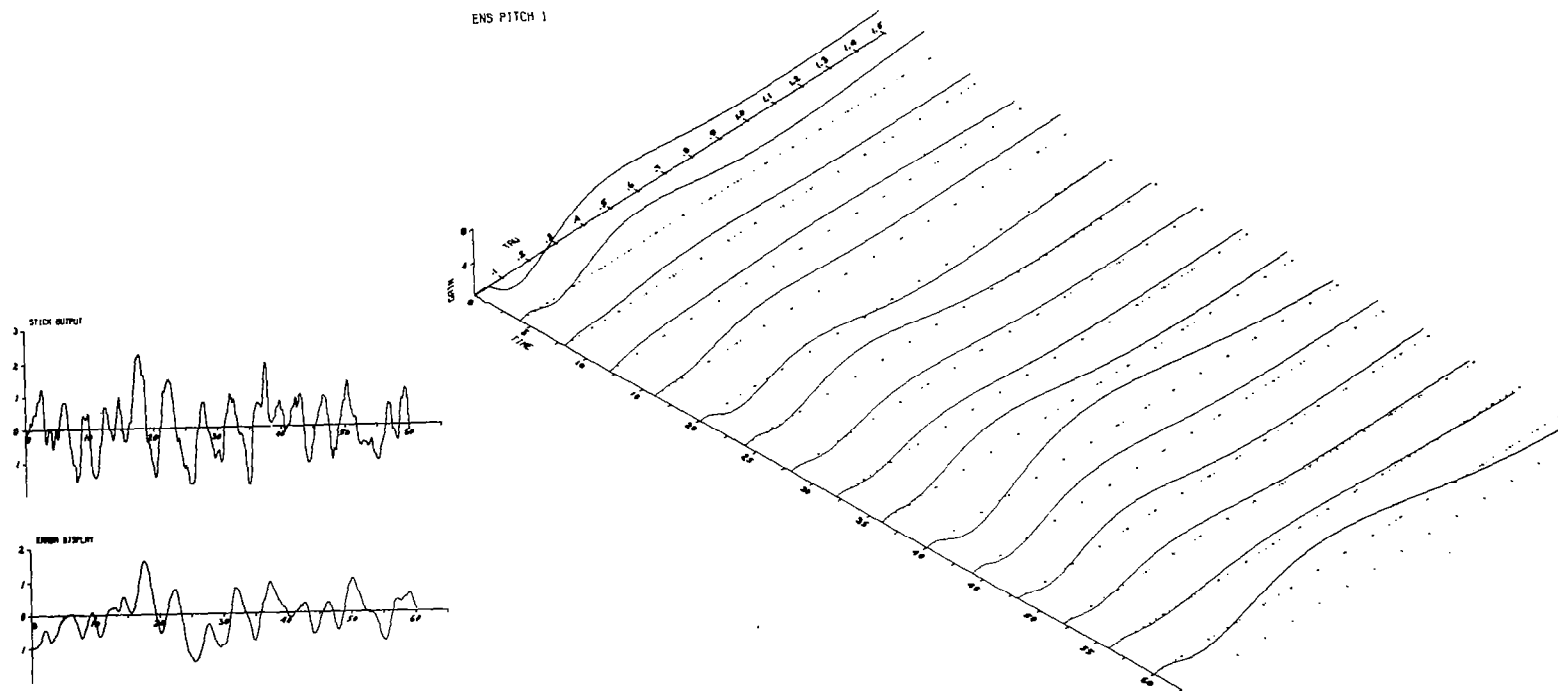


Figure 17 SPECIAL STEP RESPONSES OF TIME-VARYING  
LINEAR MODEL FOR PITCH AXIS, TASK 1,  
SPOT DISPLAY, ENSEMBLE DATA.

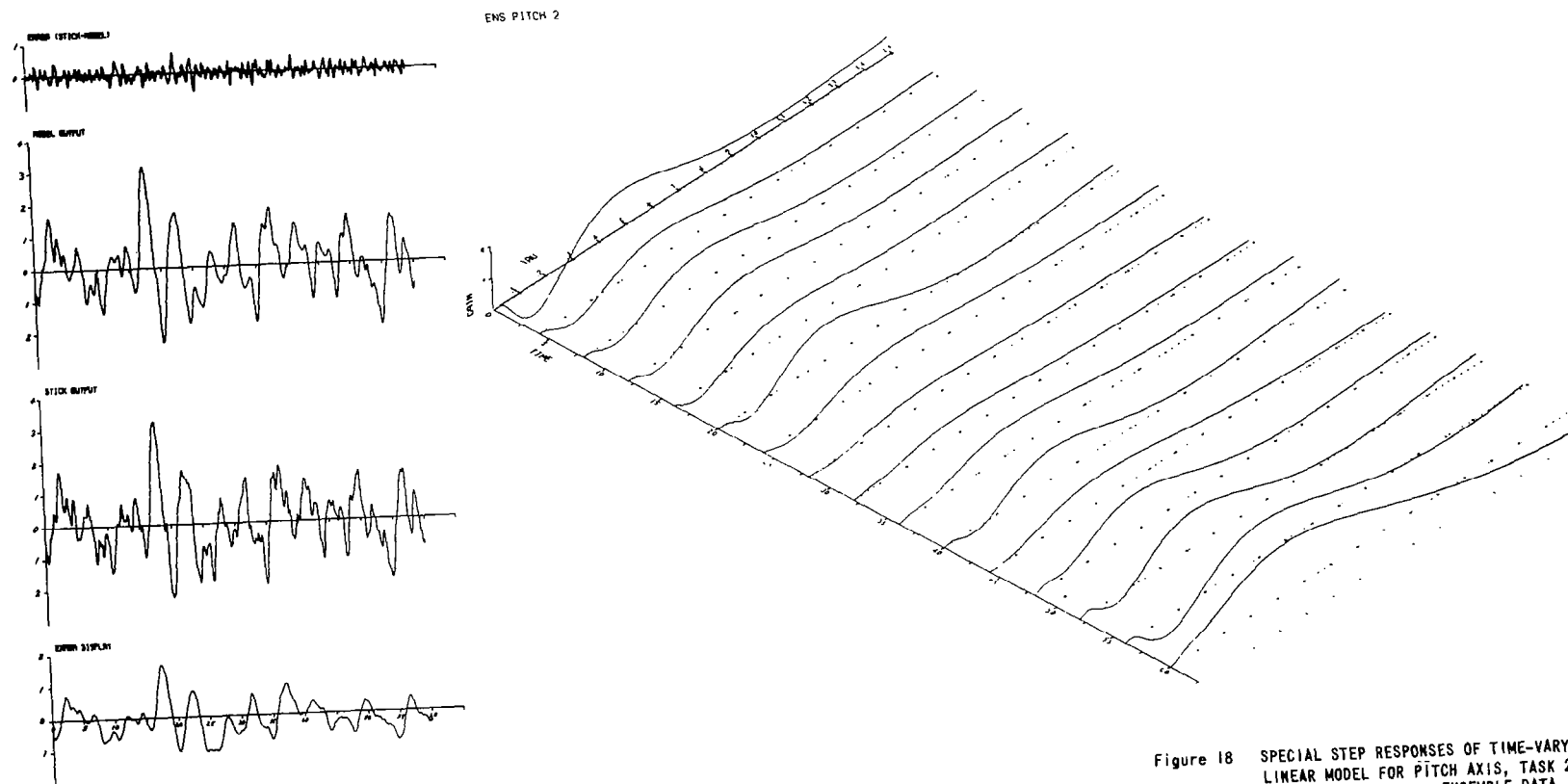


Figure 18 SPECIAL STEP RESPONSES OF TIME-VARYING LINEAR MODEL FOR PITCH AXIS, TASK 2, ARTIFICIAL HORIZON, ENSEMBLE DATA.

ENS PITCH 3

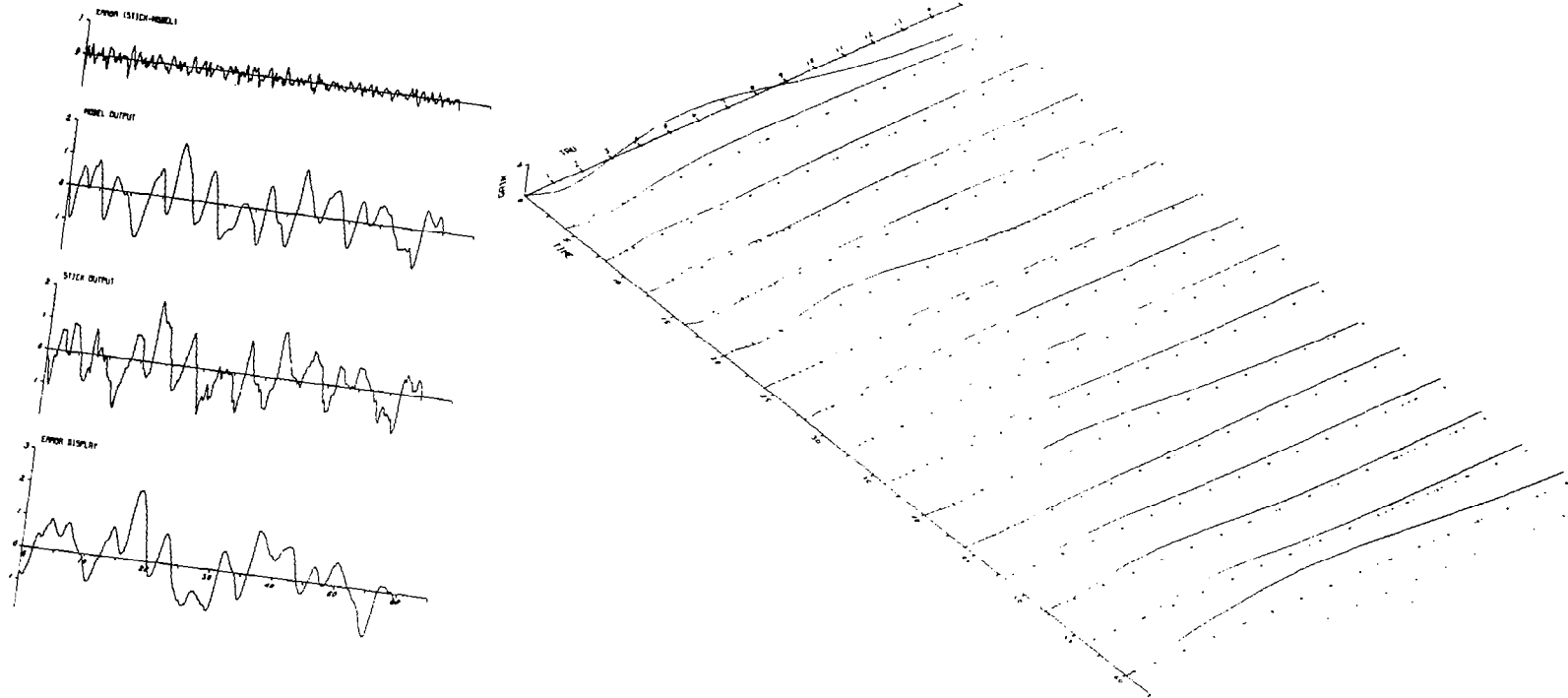


Figure 19 SPECIAL STEP RESPONSES OF TIME-VARYING LINEAR MODEL FOR PITCH AXIS, TASK 3, 2-METER DISPLAY, ENSEMBLE DATA.

ENS PITCH 4

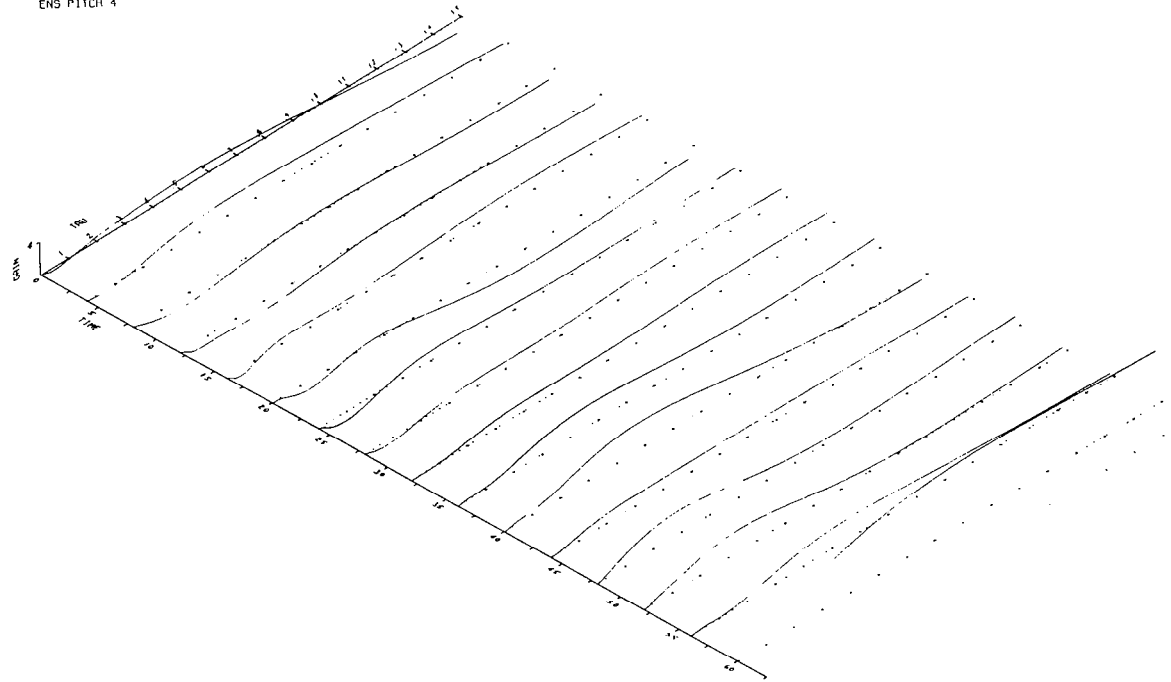
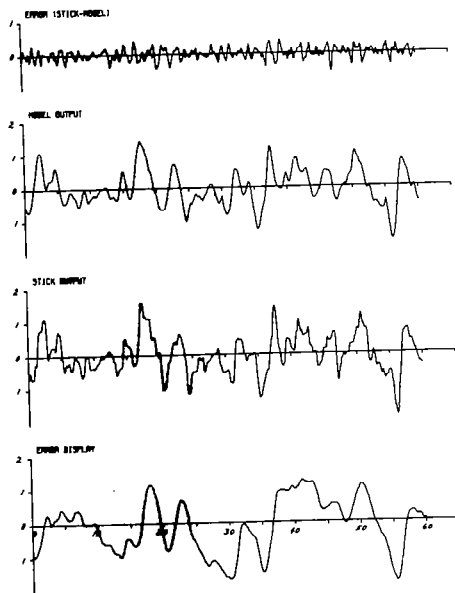


Figure 20 SPECIAL STEP RESPONSES OF TIME-VARYING  
LINEAR MODEL FOR PITCH AXIS, TASK 4,  
2-METER WITH WORKLOAD, ENSEMBLE DATA.

ENS ROLL

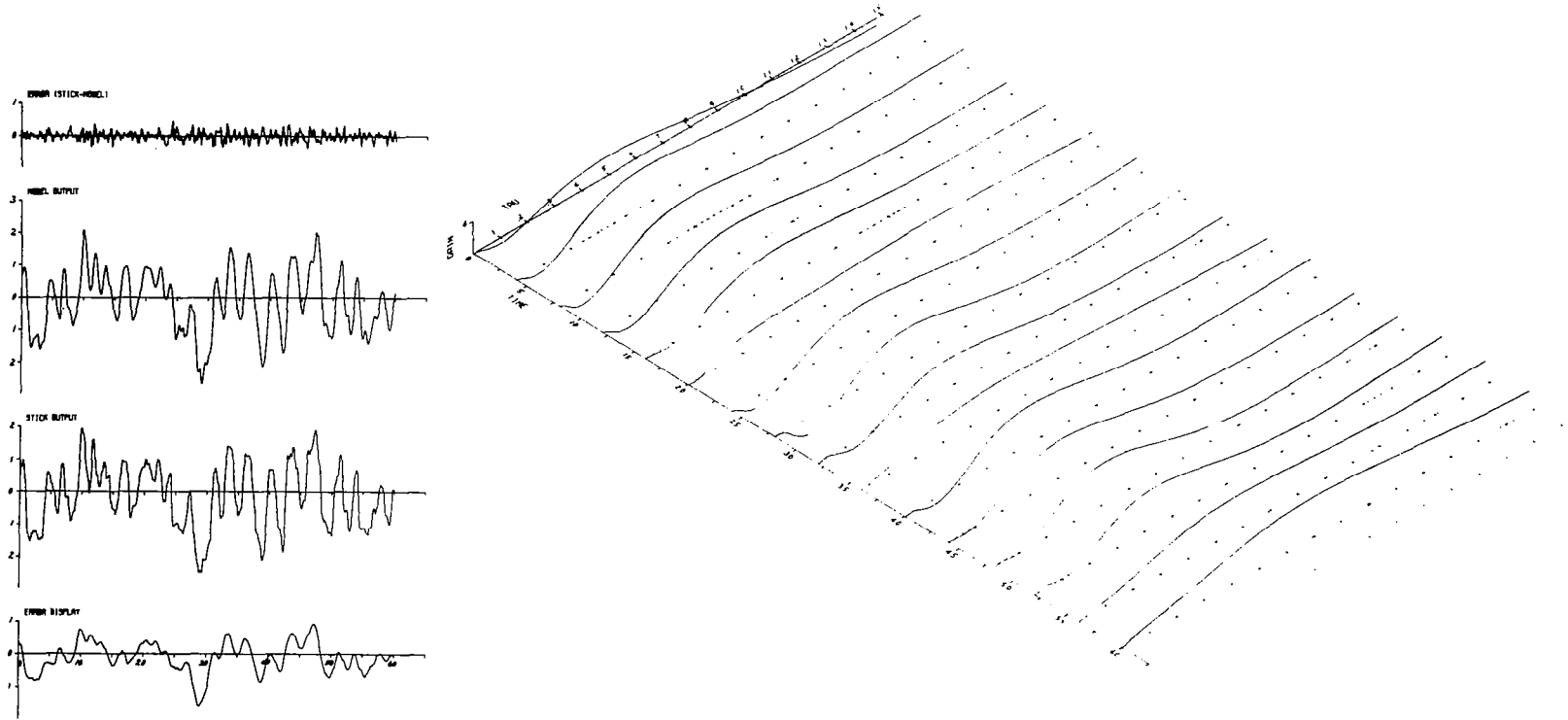


Figure 21 SPECIAL STEP RESPONSES OF TIME-VARYING LINEAR MODEL FOR SINGLE AXIS, TASK 0, IN ROLL, ENSEMBLE DATA.



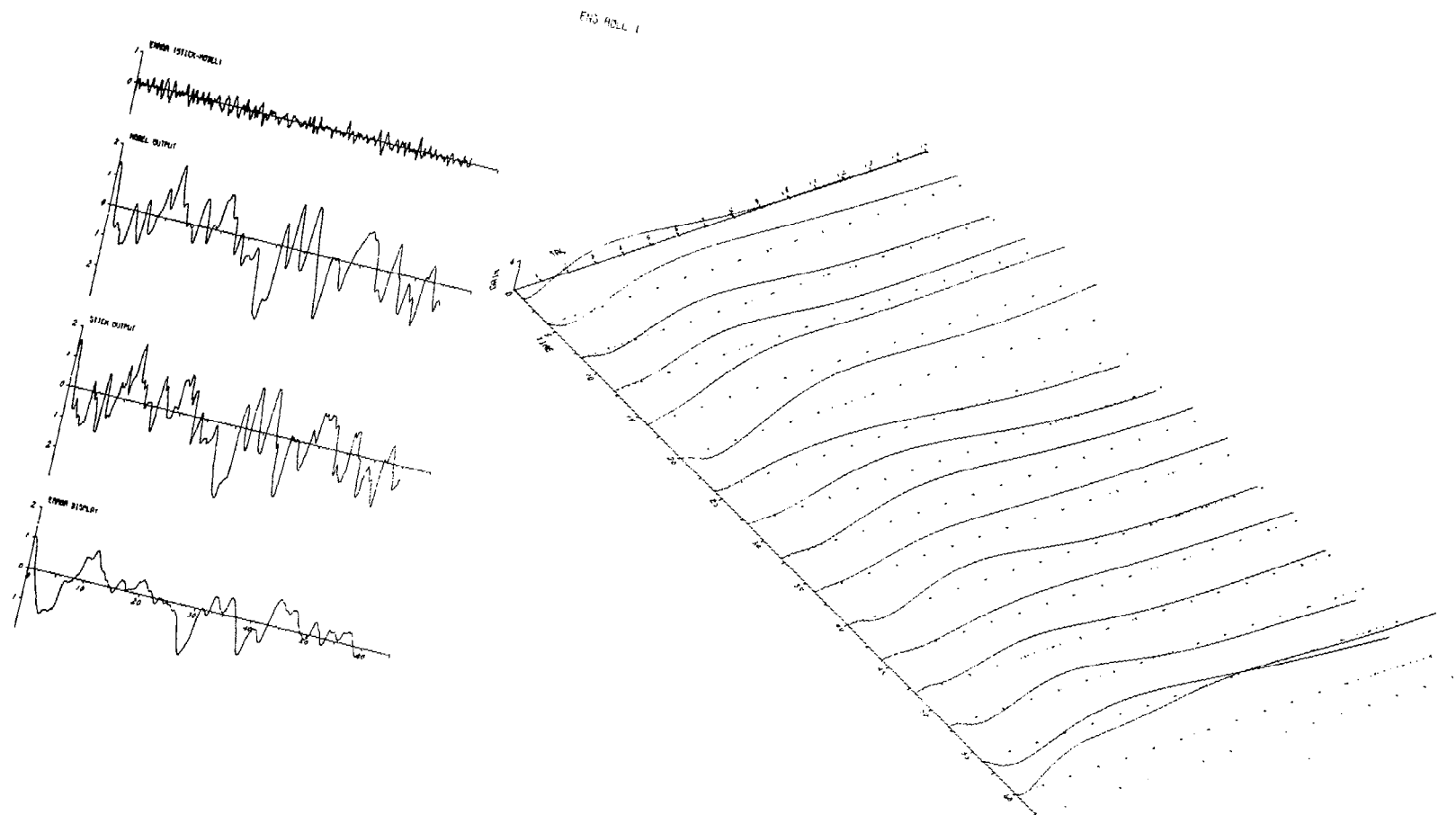
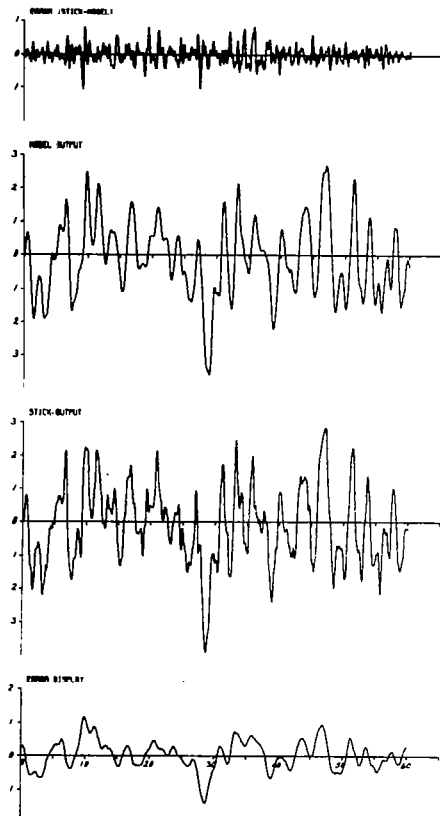


Figure 22 SPECIAL STEP RESPONSES OF TIME-VARYING LINEAR MODEL FOR ROLL AXIS, TASK 1, SPOT DISPLAY, ENSEMBLE DATA.



ENS ROLL 2

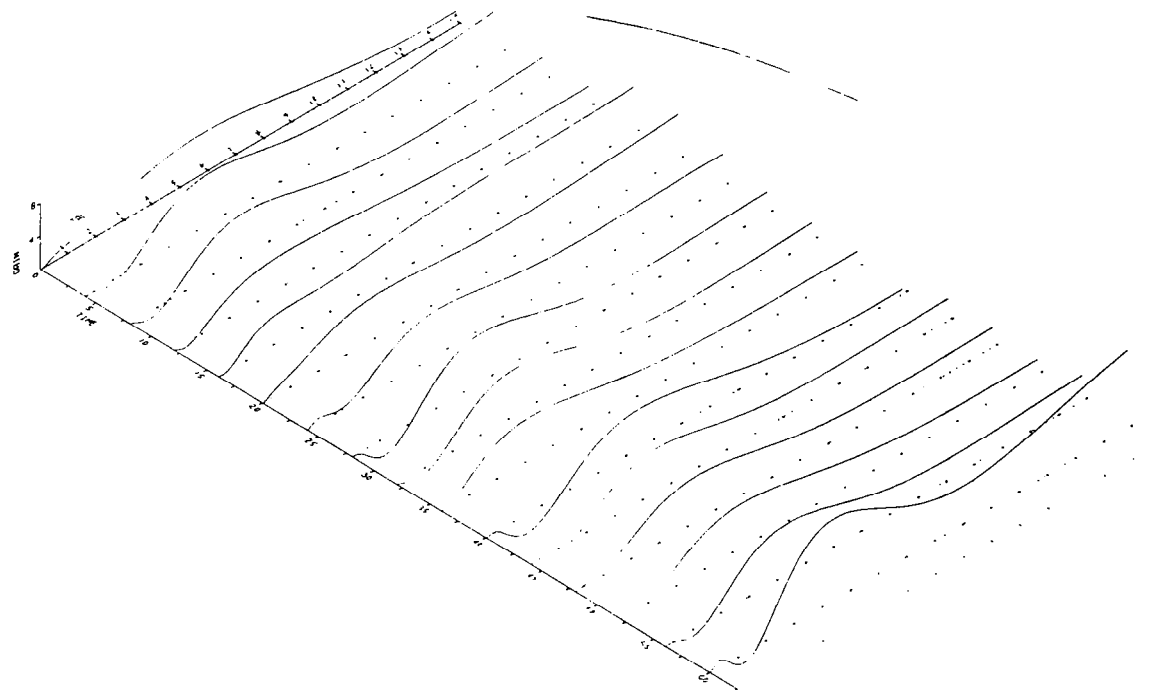


Figure 23 SPECIAL STEP RESPONSES OF TIME-VARYING  
LINEAR MODEL FOR ROLL AXIS, TASK 2,  
ARTIFICIAL HORIZON, ENSEMBLE DATA.

ENS ROLL 3

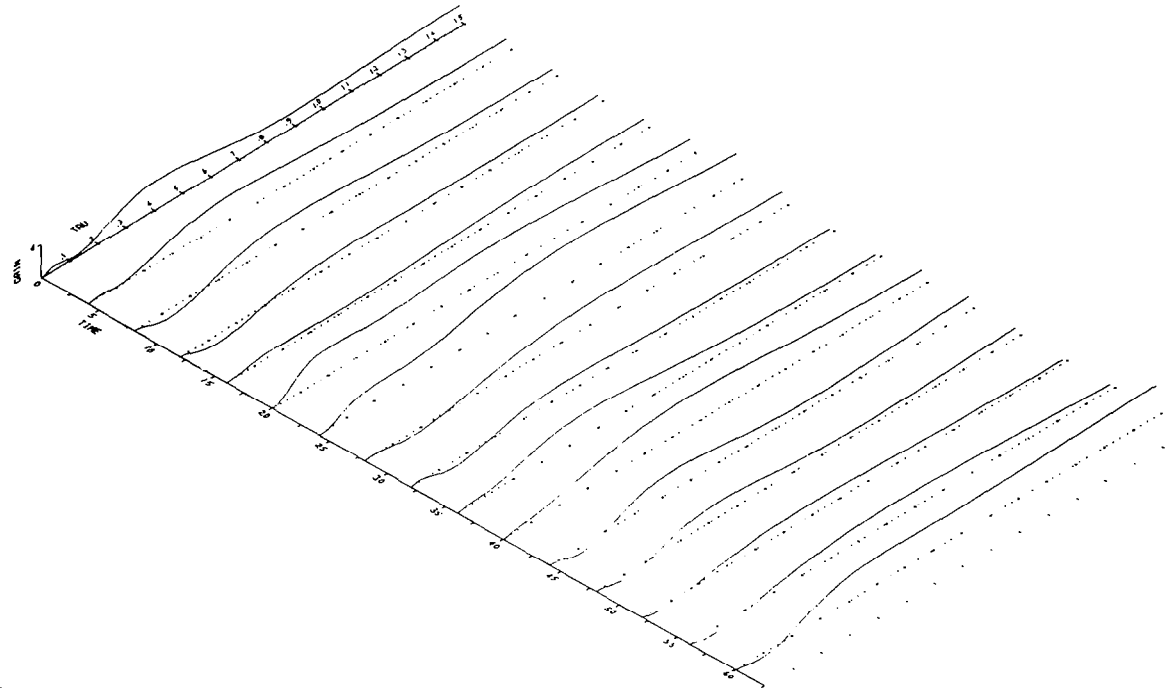
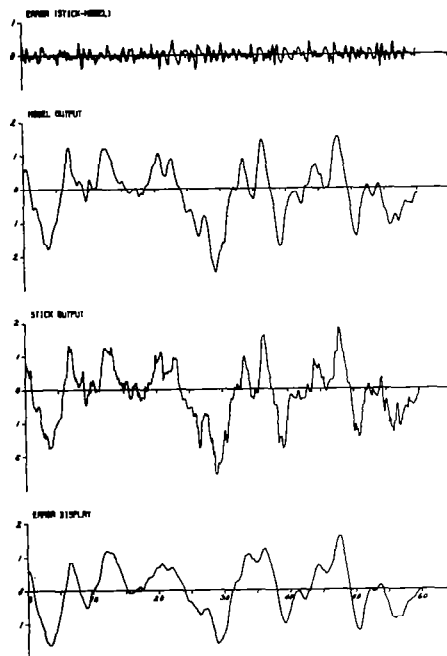


Figure 24 SPECIAL STEP RESPONSES OF TIME-VARYING LINEAR MODEL FOR ROLL AXIS, TASK 3, 2-METER DISPLAY, ENSEMBLE DATA.

ENS ROLL 4

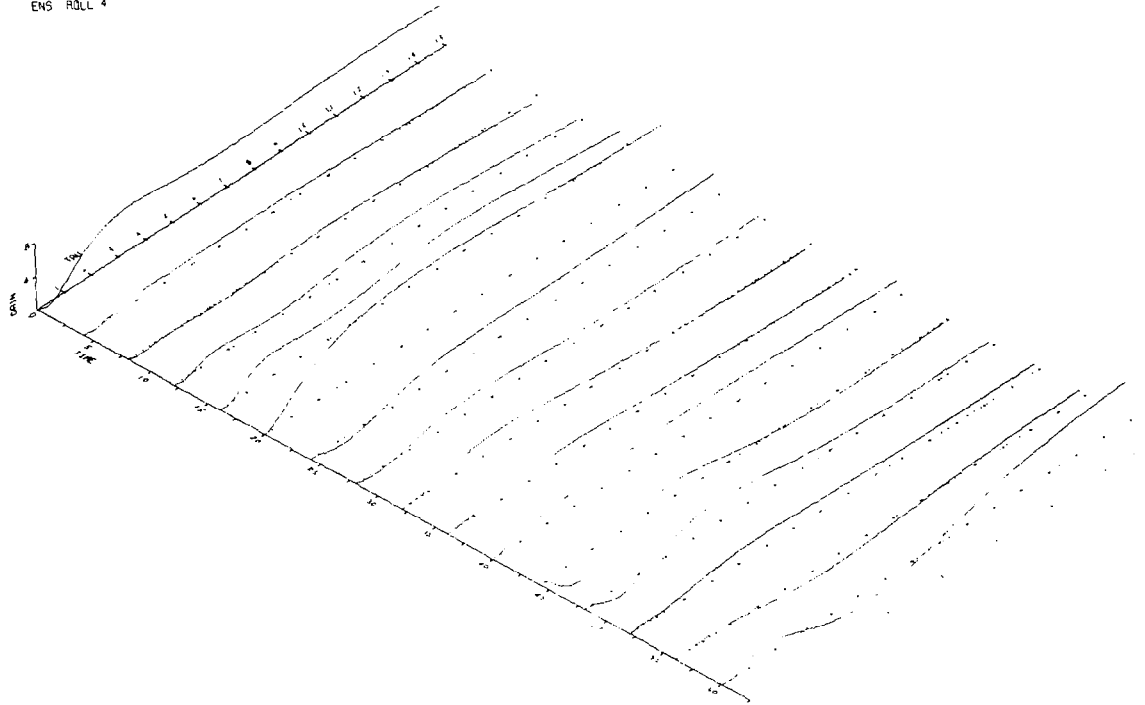
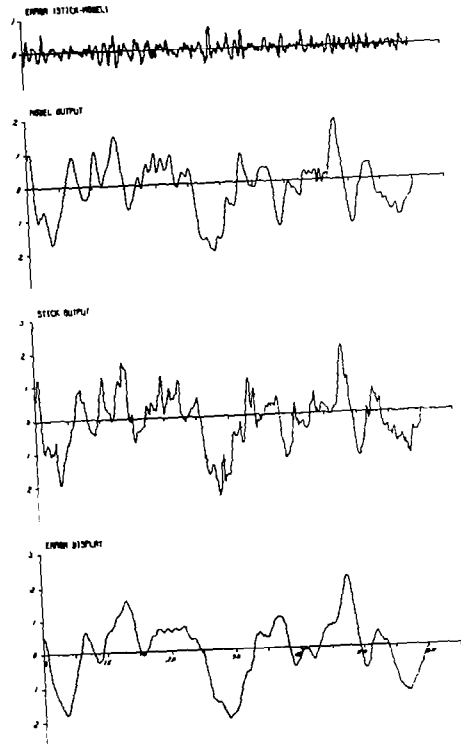


Figure 25 SPECIAL STEP RESPONSES OF TIME-VARYING LINEAR MODEL FOR ROLL AXIS, TASK 4, 2-METER WITH WORKLOAD, ENSEMBLE DATA.

2. The use of an artificial horizon or 8-ball display in tracking tasks produces responses in roll that are different from those obtained for other displays. It is seen that the stick output waveforms of Figures 13 and 23 are very different from all other pitch and roll stick output waveforms. These two roll responses, which correspond to artificial horizon tracking, show considerably less "flat-topping" and are of larger amplitude than the other stick-output waveforms. In addition careful study of the step responses in Figures 13 and 23 show that these responses are similar to each other in many ways and are also somewhat different from all other step response characteristics. Fortunately, since a research engineer was included in the experiments, the reason for the different characteristics of the two plots was discovered. The research engineer pointed out that he had learned to make automatic responses in roll when the artificial horizon was used. He found that by maintaining the control stick vector perpendicular to the horizon bar of the display, which displayed the roll axis error, he could obtain good control over the roll axis error without a great deal of effort. It can safely be concluded that all four subjects discovered this trick, and that this automatic response on their part produced a different type of transfer characteristic than was normally obtained.
3. A somewhat more tentative conclusion can also be reached about the roll axis responses for the artificial horizon. Because of the similarity between the individual and ensemble roll responses

using the artificial horizon, it appears that all four subjects were responding in nearly the same way; that is, their stick-output waveforms were very similar. Accordingly, a tentative conclusion may be drawn that less intersubject variability will occur in the stick-output data if the tracking task can be designed so as to allow a "mechanical" or "automatic" response on the part of the operator. Further experimentation on this subject would be desirable and perhaps rewarding.

4. The time-variability of the transfer characteristics increases with task complexity. Both pitch and roll axes in the individual and ensemble runs exhibit a trend toward this greater variability with task complexity. However, in order to observe this trend, it is first necessary to properly assess task difficulty. The particular problem in this regard is to properly assess the difficulty of Task 2 wherein the artificial horizon was used. It is necessary to account for the mechanical responses encountered in roll and to assess this effect on the pitch axis.

A rating scale that describes the degree of difficulty was chosen. The number 0 indicates an effortless task and 10 indicates a very difficult task. The tasks were then rated in difficulty by the research engineer who participated in the experiment. His ratings are given below, with the exception of Task 2 in roll. It was felt that because the response in this task was of an entirely different nature that it should not be included in this evaluation. Task 2 in pitch was rated only slightly more difficult than Task 0 because

nearly full attention could be given to the pitch axis in performing Task 2. Similarly, Task 3 was rated only slightly more difficult than Task 1, because Task 3 required greater eye motion but otherwise was nearly the same as Task 2.

If one arranges the plots of the time-varying step responses for individual pitch, individual roll, ensemble pitch, and ensemble roll in an order of increasing task difficulty as given by Table 4, one sees a very definite trend toward increased variability with task difficulty. This trend is particularly well illustrated by comparing Tasks 3 and 4. In all four cases (that is, individual pitch and roll, and ensemble pitch and roll) greater variability occurs when the extra workload is added. Unfortunately, time and circumstances did not allow a more mathematical assessment of variability of the step responses.

5. It is easily shown that the individual pilot will produce control stick motions called "flat-topping" motions that are peculiar to the run under consideration, and become lost in the ensemble average. Flat-topping may be regarded as that property in the human's response which causes him to pull the control stick over and hold it at a constant displacement until the error is driven to zero. The stick output waveform of Figure 9 exhibits this flat-topping very clearly. All of the individual runs (Figures 6 through 15) with the exception of Task 2 in roll (Figure 13) exhibit the flat-topping phenomenon.

Table 4  
RELATIVE RATINGS OF TASK DIFFICULTY

TASK	RATING	
	PITCH	ROLL
0	2	2
1	5	5
2	3	-
3	6	6
4	8	8



The interesting point in regard to flat-topping is that it is almost completely removed by ensemble averaging. The stick-output waveforms of Figures 16 through 25 show essentially no evidence of ensemble flat-topping. It may therefore be concluded that the subjects were not performing flat-topping at the same times and at the same levels, so that the individual effect becomes lost in the ensemble average.

A comparison of Tables 2 and 3 shows that the characterization of the individual by a linear time-varying network will result in a greater characterization error than characterization of an ensemble by a linear time-varying network. The flat-topping phenomenon is clearly the result of a nonlinear operation on the display error signal. Thus, it would seem that the individual response would contain greater nonlinearity than the ensemble response. Accordingly, a larger linear characterization error for individual data is to be expected, and does indeed occur.

6. There appears to be no deterministic mechanism for explaining the linear time-variability of the human operator. In the study of the time-varying step responses and time waveforms presented in Figures 6 through 25, a major effort was made to explain, if possible, the causes of the time-variability in these step responses. In other words, an attempt was made to relate the time-variability by means of a fixed set of rules to the various signals in the system, for example, input, error, stick output, or system output signals. If such a set of rules exists and could be determined,

then time-varying models with their considerably smaller characterization error (over linear constant-coefficient models) could be used for more precise design of manual control systems.

It is significant that this study was unable to discover any conclusive evidence of the existence of a fixed set of rules to explain the time-variation deterministically. It appears that no relatively simple function of the various system signals will predict which of the several characteristics the human operator will select for any particular short period of time.

There is some evidence to show that no set of fixed rules is capable of specifying the time-variation without a considerable average error. Consider the case in which a human operator is performing a tracking task such as that specified as Task 1 herein. After a brief period of time, precisely the same tracking task is repeated using the same human operator. Then, even if learning and fatigue are insignificant factors, the human operator does not respond in the same manner for the two experiments. There are distinct differences between the two stick-output waveforms. In addition, differences will exist between the two time-varying characterization models. It may be concluded from this example that the human operator's tracking strategy does not remain totally constant. Accordingly, one cannot expect to explain the time-variations of the operator by a set of fixed rules, without having significant errors.

A potential approach that is related to the above discussion might be used to advantage in modeling the human operator. Suppose that the time-variations in the human operator's characterization are not deterministic, but rather, occur within certain statistical expectations. Further, suppose that some type of statistical sequencing (for example, a Markoff process) relates the transfer characteristic at one time to the transfer characteristic a short time later. Under these circumstances it would be possible both to describe the time-variations in the transfer characteristic of the human operator on a statistical basis and to produce "typical" time-varying human operator transfer characteristics. Thus, an investigator could construct a model of a human operator whose time-variations statistically match those of the human operator's dynamical time variations. The examples of word and sentence construction given in Reference 11 explain the philosophy of this proposed approach.

### Nonlinear Time-Varying Models of the Human Operator

For a number of years investigators in manual control systems have been of the opinion that the human operator in a control task exhibits both nonlinearity and time-variability. However, because of a complete lack of analysis and synthesis methods for nonlinear time-varying systems, virtually nothing could be done about investigating the human as a nonlinear time-varying system. Clearly, it would be very advantageous to understand these phenomena as they occur in the human operator. Because of this complete absence of previous work, and because the deterministic theory developed under the

previous contract is capable of dealing with nonlinear time-varying characterizations with the same facility as linear time-varying characterization, a small initial study was performed for the nonlinear case.

Two characterization runs were made, one for the single axis pitch task (Task 0) and one for the pitch axis of the two-axis compensatory task (Task 1). It was decided to use individual data only, since the individual data appeared to possess greater nonlinearity (as a result of flat-topping). The class of nonlinear filters used for this study is described in Chapter II.

Presentation of the results of the nonlinear time-varying characterizations is given in two parts. The first part is embodied in Table 5 in which the characterization errors for the linear time-varying and the nonlinear time-varying cases are compared. This table shows that the nonlinear time-varying models contain only slightly more than half the error contained in the corresponding linear time-varying models. The second part of the characterization results are found in Figures 26 and 27 wherein the stick-output and the nonlinear time-varying model output waveforms<sup>\*</sup> may be directly compared. It is seen that the time-varying nonlinear model's output is remarkably similar to the human's output. A comparison of this model output with the linear model outputs (Figures 6 and 7), shows that an important degree of improvement is possible with the use of nonlinear time-varying models.

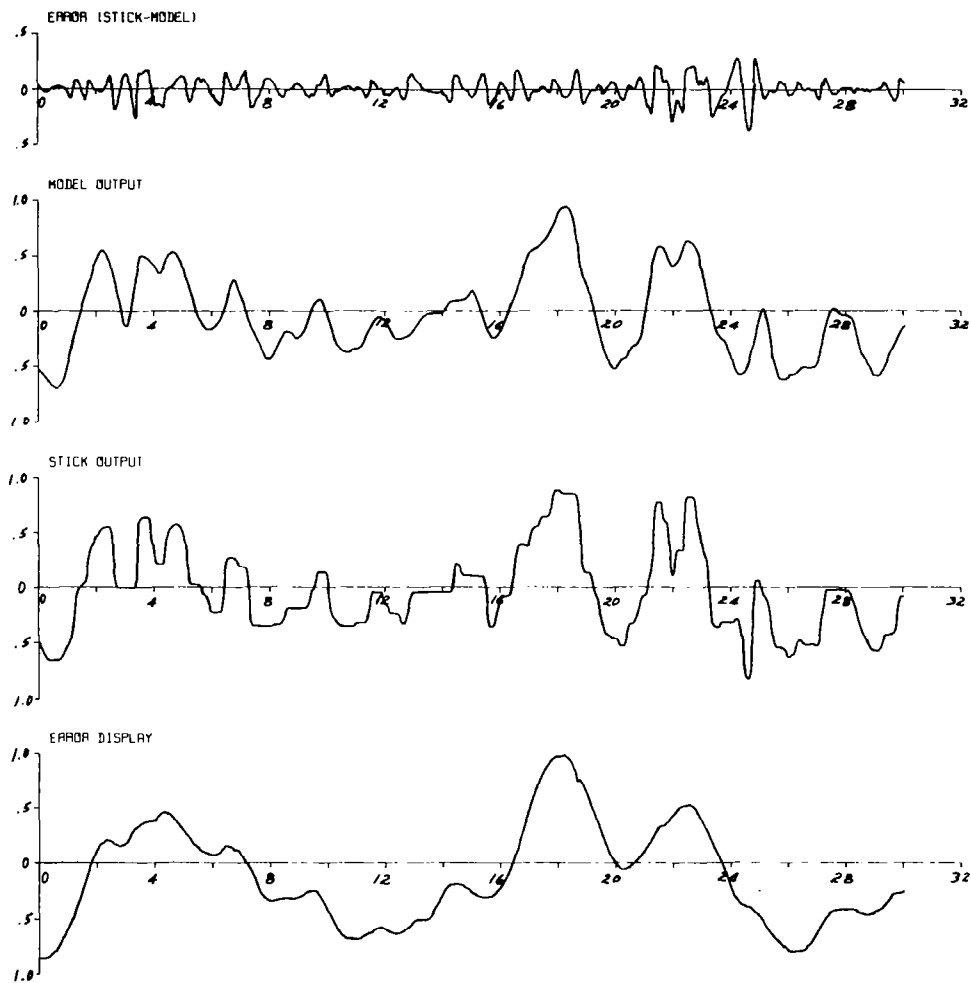
---

\*The complexity of the nonlinear digital program and the increased data storage requirements necessitated a reduction in the time length of the signals processed. Consequently, only 30 seconds of data were analyzed.

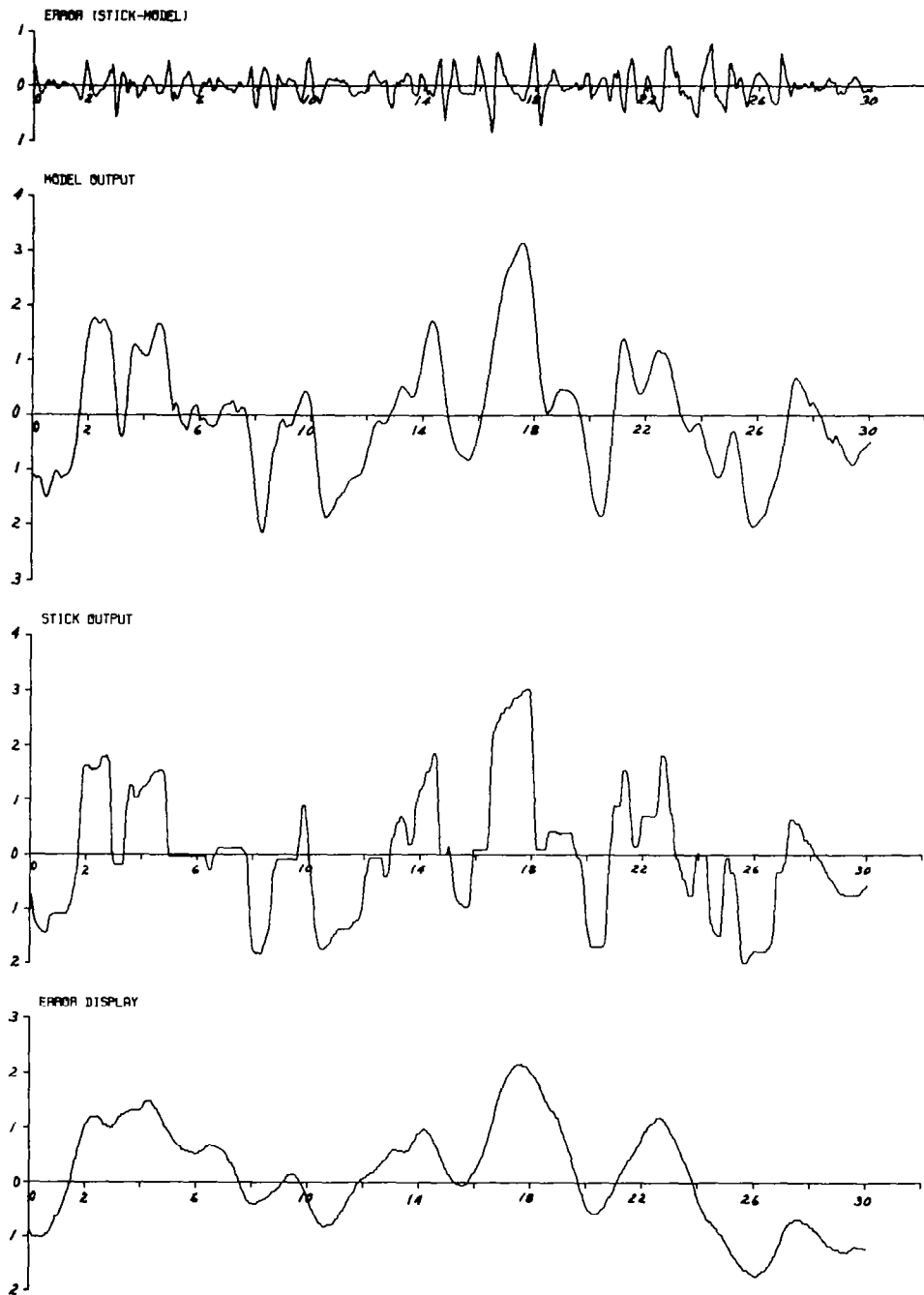
It should be mentioned that the actual time-varying transfer characteristics are not presented in this report because they cannot be plotted isometrically. These nonlinear characteristics require six dimensions and therefore can only be presented in numerical form.

Table 5  
COMPARISON OF CHARACTERIZATION ERRORS BETWEEN  
LINEAR AND NON-LINEAR MODELS

TASK	DISPLAY	NO. OF AXES	LINEAR MODEL		NON-LINEAR MODEL	
			% N.I.S.E.	FIG. NO.	% N.I.S.E.	FIG. NO.
0	SCOPE	1	9.71	6	5.80	26
1	SCOPE	2	8.44	7	4.45	27



**Figure 26** TIME HISTORIES OF THE TIME-VARYING NONLINEAR MODEL FOR THE SINGLE AXIS, TASK O, IN PITCH.



**Figure 27** TIME HISTORIES OF THE TIME-VARYING NONLINEAR MODEL FOR THE PITCH AXIS OF TASK 1, SPOT DISPLAY.

## V. LOGIC MODEL STUDY OF TRACKING DATA

In Chapter I of this report, a "logic model" is defined as a model of the human operator that simulates the logic strategy that the human operator may exhibit while tracking in a control system. A logic model is therefore fundamentally different in concept from a describing function model, for example. A describing function model is obtained by matching the output of a linear constant coefficient filter to the stick-output produced by the human operator. In contrast, a logic model is used to mimic the strategy of the human operator in performing a tracking task. Thus, a logic model is generally a nonlinear device which contains decision elements as well as dynamical components.

The development of a logic model is a difficult task because it is generally necessary to resort to intuitive or trial-and-error procedures. The approach that has been used previously is that of guessing at the strategy and then matching the model output to the human's output by parameter adjustment on the analog computer. This approach is certainly a valid one, but it leaves several important questions unanswered. Most important among these is the question of what is the best possible logic model that can be developed and further, how does a particular logic model, developed experimentally, compare with this "best" logic model.

In Chapter IV it was stated that the human operator will not respond in exactly the same manner if a particular tracking task is repeated with the same input signals. Failure to repeat his earlier performance exactly indicates that his tracking strategy has changed or evolved into a new form.



This variation in his strategy, unless it is predictable, will fix a bound on the accuracy of characterization of any fixed-strategy logic model. Thus, the question arises as to whether the accuracy of fixed-strategy logic models may be made to approach that of time-varying linear models.

A thorough investigation into the problem of logic models would have the following objectives:

- (1) the determination of the possible bounds or limits on the accuracy of fixed-strategy logic models.
- (2) the development of a logic model form that exhibits a potential for further development into the ultimate logic model.
- (3) the development of a practical logic model that has reasonable accuracy.

Because of the high priority of the time-varying characterization study it was necessary to limit considerably the scope of the logic model study.

Consequently, the first objective was chosen because of its importance as a guideline for future work on logic models and also because it is possible to study the problem within the framework of the deterministic characterization.

A logic model is actually a nonlinear constant-coefficient filter that maps the displayed signal into a close approximation of the human operator's output signal. Therefore, if a sufficiently general nonlinear characterization of the human operator can be obtained, the accuracy of characterization must approach that of the best logic model. In other words, a logic model is

necessarily one member of a larger class of nonlinear constant-coefficient filters. The best logic model is also the best nonlinear filter in the large class of nonlinear filters.

The deterministic theory developed on the previous contract is well suited for studying nonlinear time-varying models of the human operator. It follows, that by using a degenerate case, the theory can be readily applied to obtain nonlinear constant-coefficient models. The constant-coefficient nonlinear case is merely the one extreme condition explained in the theory in which all information about the human operator's time-variation is suppressed.

The question must now be answered as to what class of nonlinear constant-coefficient networks is sufficiently general as to encompass all practical logic models that might be devised. This is a difficult question and the answer is impossible to verify. Apparently, the best that can be done is to choose a very general class of nonlinear filters, wherein members of the class are known to exhibit responses similar to those of the human operator. If the class is sufficiently general as to approach a large class of pattern classification devices, then it should be capable of determining the ultimate accuracy of logic models.

The class of filters chosen for the study was composed of the multiplied outputs of a set of Kautz filters followed by nonlinear zero-memory power law devices. The seven Kautz filters used in the linear time-varying characterizations discussed in Chapter II were used. These seven Kautz filter outputs were then multiplied together in various ways to increase the number of outputs. If a given Kautz filter is designated by its number, then

the outputs of the filters were generated as follows: 1, 2, 3, 4, 5, 6, 7, 1 x 2, 2 x 3, 3 x 4, 4 x 5, 5 x 6, 6 x 7, 1 x 4, 2 x 5, 3 x 6, and 4 x 7. Thus a total of 17 outputs from the Kautz filters were generated. Each one of these 17 filters was then applied as an input to four power law devices. In particular, each given member output of the 17 outputs was taken to the first, second, third, and fifth powers. Accordingly, a total of 68 linear and nonlinear operations on the display signal were used to make up the nonlinear model. The characterization process consisted of choosing the optimal set of 68 fixed gains, which when multiplied by the 68 outputs and the result summed would produce the least integral squared error. It is believed that the fixed-form filter upon which the characterization was based has sufficient flexibility to enable it to simulate any strategy likely to be used by the human operator, and that characterization with this filter borders on what may be termed pattern classification.

Two computer runs were made using the nonlinear constant coefficient models. A special form of the deterministic theory program was developed for these two runs. A computer run was made for the single axis pitch task (Task 0), and another run was made for the pitch axis of the two-axis compensatory task (Task 1). The experiments were limited to individual data, since logic models are not presently being considered for ensemble data.

Presentation of the results of these two computer runs are given in Tables 6 and 7, and in Figures 28 and 29. Tables 6 and 7 include all computer results on % N.I.S.E. for the two sets of data, and Figures 28 and 29 are plots of the waveforms including the outputs of each optimum nonlinear constant-coefficient model.

Table 6  
CHARACTERIZATION ERRORS FOR THE 3 TYPES OF MODELS.  
PITCH AXIS, TASK 0. INDIVIDUAL PILOT, SINGLE AXIS.

MODEL	% N.I.S.E.	RESPONSES PLOTTED IN
TIME-VARYING LINEAR	9.71	FIG. 6
TIME-VARYING NONLINEAR	5.80	FIG. 26
CONSTANT COEFFICIENT NONLINEAR	19.6	FIG. 28

Table 7  
CHARACTERIZATION ERRORS FOR THE 3 TYPES OF MODELS.  
PITCH AXIS, TASK 1. INDIVIDUAL PILOT, 2-AXIS.

MODEL	% N.I.S.E.	RESPONSES PLOTTED IN
TIME-VARYING LINEAR	8.44	FIG. 7
TIME-VARYING NONLINEAR	4.45	FIG. 27
CONSTANT COEFFICIENT NONLINEAR	15.5	FIG. 29

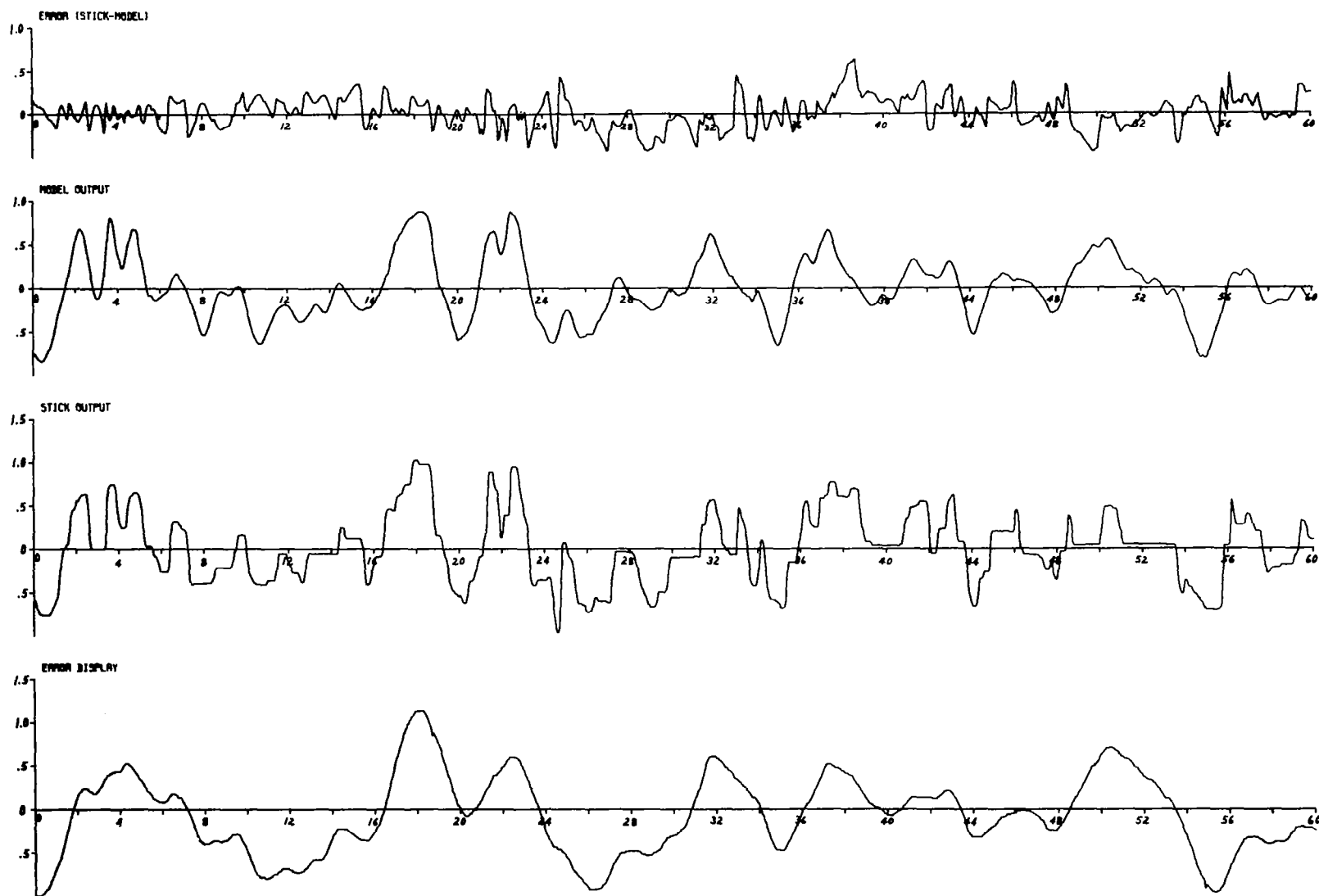


Figure 28 TIME HISTORIES OF THE CONSTANT-COEFFICIENT NONLINEAR MODEL FOR THE SINGLE AXIS, TASK 0, IN PITCH.

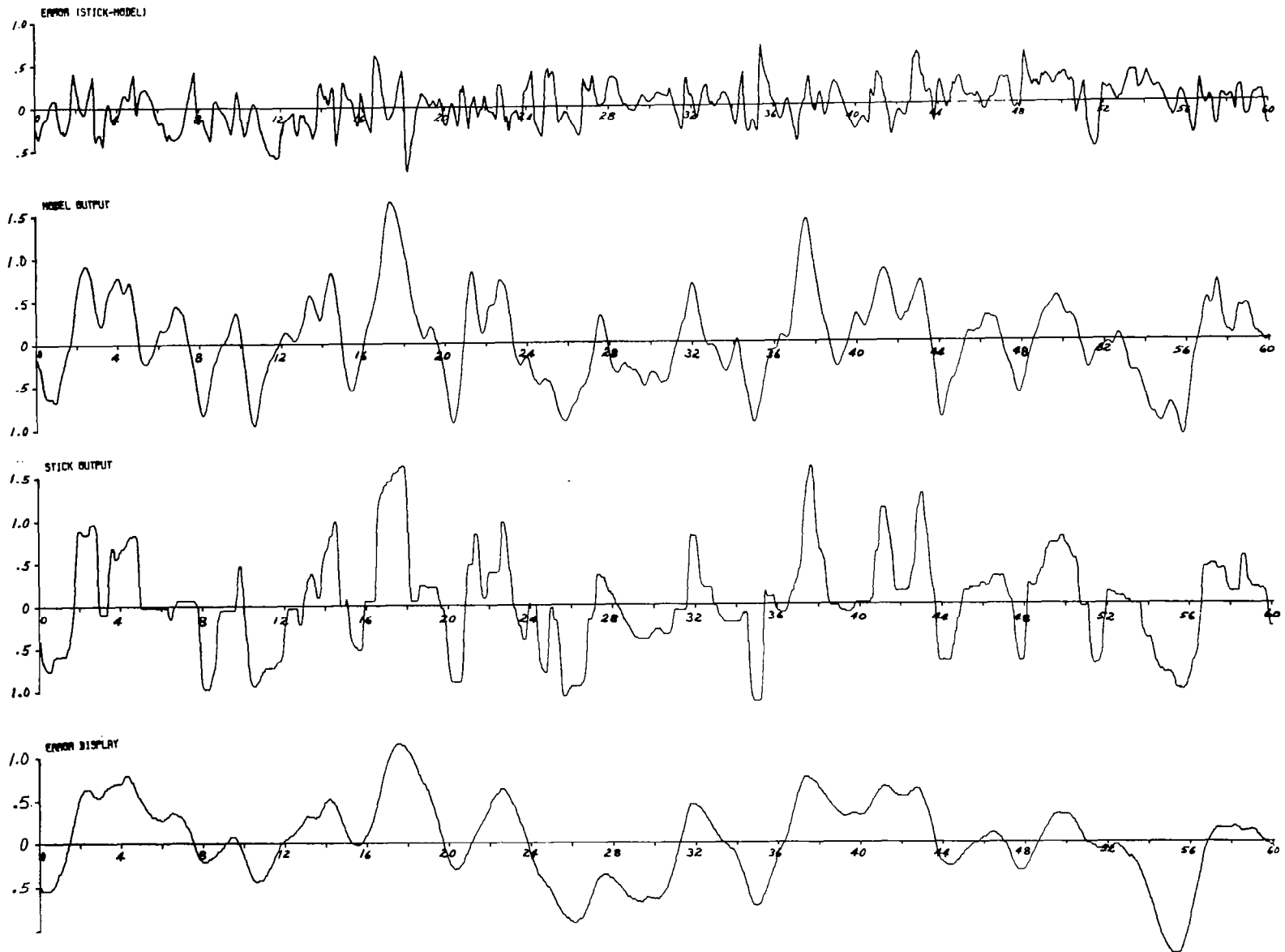


Figure 29 TIME HISTORIES OF THE CONSTANT COEFFICIENT NONLINEAR MODEL FOR THE PITCH AXIS OF TASK 1, SPOT DISPLAY.

The tables show, that although the nonlinear constant-coefficient models have larger error than either the time-varying linear or time-varying nonlinear models, they are definitely superior to linear constant-coefficient models (which at best would have 35 to 45% N.I.S.E.\*). Since the nonlinear constant-coefficient models represent the ultimate capability of logic models, it may be assumed that the best logic models will operate with errors on the order of 15 to 20% (N.I.S.E.). Since linear constant-coefficient models rarely if ever possess an error of less than 35% (N.I.S.E.) it appears that improvement by a factor of two in the error is possible by using logic models instead of linear constant-coefficient models.

An inspection of the output waveforms in Figures 28 and 29 show that the optimum nonlinear constant-coefficient models are reasonably accurate in approximating the stick-output of the human operator. However, it is clear also that these nonlinear filters do miss important fine-grain features of the human operators' output. It may be concluded that fixed-models, even though highly sophisticated and very nonlinear, will be unable to account for all of the human operator's output. Nevertheless, an important degree of improvement is possible by use of a logic model.

The results of this study, although preliminary, can serve as a measure against which further developments of logic models may be compared. Based upon the results presented in this chapter it may be stated that if a logic model is developed for an equal length of similar data and it produces errors of 20 to 25% N.I.S.E., the logic model can be considered a good one.

---

\*These figures were obtained from results of the previous study (NAS 1-3485) and from extrapolations of data presented in the literature. Exact comparison with the many reported methods is impossible because of the dissimilarities in experimental procedures and methods.

## VI. CONCLUSIONS AND RECOMMENDATIONS

In this study three different classes of models have been used to characterize the human operator in one- and two-axis tasks. Linear time-varying and nonlinear time-varying models have been used extensively to study the time-variations and non-linearities in the dynamics of human pilots. The results have been presented in the form of time-varying step responses of the human pilot. In addition, highly complex nonlinear constant-coefficient models have been developed to examine the possible theoretical limits of accuracy that can be achieved with logic models.

This study has shown that important and significant gains in accuracy can be attained by using these newer models. In fact, for the nonlinear time-varying case where the modeling error is roughly 5% (N.I.S.E.) it is most unlikely that the remaining error between the model and the human will have any appreciable effect on the control system or its output. It is therefore suggested that further studies of the nonlinear time-varying models be conducted to realise their potential for the synthesis of improved manual control systems.

Several rules which explain to some degree the way in which the human operator responds have been obtained by this study. First, the human operator often exhibits a nonminimum phase characteristic. This characteristic is apparently the result of reaction time and has in the past been approximated by a pure delay. Secondly, the use of an artificial horizon or 8-ball display causes the operator to respond in a significantly different manner from what is usually obtained. This unusual somewhat mechanical response is attributed to the operator's application of a simple rule, based



upon the relative geometry of the horizon bar and the control stick position. Thirdly, it was found that the time-variability of the linear models generally increased as task complexity was increased. This rule seems to corroborate the result of other investigators, wherein remnant power increases with task complexity.

Another interesting phenomena studied in detail was the "flat-topping" that appears in the trace of the human operator's stick output. This characteristic was found to be a highly individualistic nonlinear effect with very little intersubject correlation since its appearance in the ensemble data was almost nonexistent. Nonlinear time-varying characterization models are able to account for a significant portion of the flat-topping phenomena, since these models can assume new nonlinear characteristics in a relatively short period of time.

There appears to be no simple relationship between the time-variations of the linear time-varying transfer characteristics and the signals of the corresponding manual control system. Although a great deal of effort was focused on trying to find such a relationship, it now seems to us that the individual time variations are a function of the biological mechanism of the human operator and are caused by such phenomena as fluctuations in attention, motivation, and general random drifting of biological characteristics. As supporting evidence that the above conclusion is correct, we cite the example that the human operator does not identically repeat his performance in any particular tracking experiment. Thus his fluctuations are random functions of time and are not strict functions of the system signals.

Nonlinear constant-coefficient models of a highly complex nature were used to place a bound on logic model accuracy. The reasoning in this case is that a logic model is really a nonlinear constant-coefficient filter of a special type. Therefore, the optimal filter in a general class of nonlinear constant-coefficient filters will possess approximately the same accuracy as the best logic model. The results for a 68 element nonlinear filter show that optimal logic models will probably possess errors on the order of 15 to 20% (N.I.S.E.).

It should be mentioned that this study describes the first application of any type of nonlinear synthesis to manual control problems. Thus, the characterization of the human operator by nonlinear constant-coefficient and nonlinear time-variable models as reported herein is totally original work.

It should also be mentioned that the solution of the optimal filter by the deterministic characterization method, as applied in this study, is convergent and completely free of computational instabilities. Optimal time-varying linear and nonlinear filters as well as constant-coefficient nonlinear filters have been derived with relatively equal ease.

Several recommendations can be made regarding future work in manual control. These recommendations cover a wide range of topics and are largely based upon the results of the study described herein. However, some of the topics involve ideas that were generated in the course of this study, but are not closely related to the subject matter of this report. All recommendations are given in the following paragraphs.

The fact that the human operator does not respond in the same way twice to precisely the same tracking situation is a cause of some concern,

for it places a lower bound on the fidelity of human operator models. It would seem appropriate to investigate this variation from run to run using carefully controlled experimental procedures to insure valid results. If such a study were run, an investigator would be in a far better position to decide what portion of the human operator's output is truly a random (or remnant) signal and what portion is the result of time-varying dynamics. At the present time, no experimental investigation has been performed to resolve this problem.

A somewhat related subject is the question of the constraints on the solution of the time-varying parameters of the model. Selection of the period or time base of the interpolation functions determines the time-variability that the model can exhibit. Since the time-variability and the characterization error are directly related by a fundamental uncertainty it seems imperative that studies be conducted to further investigate the required compromise and determine empirical rules for selecting the right amount of time-variability.

The present study showed that logic models with accuracies of 15 to 20% N.I.S.E. are theoretically possible. The nonlinear filter which was synthesized in order to obtain this result had 68 linear and nonlinear component filter outputs, and therefore is too complicated to yield intuitive information about the logic-strategy of the human operator. There are, however, certain classes of nonlinear filters which will allow an investigator to insert his intuitive ideas about the human operator's strategy directly into the model without sacrificing the automatic synthesis procedures developed in the deterministic characterization theory. Thus, the investigator may

choose the form of model (within a certain class) and determine values for the optimal parameters through application of the deterministic characterization theory. If the performance of the model is unsatisfactory then certain parts may be changed and the process repeated. In this way, a completely intuitive optimal logic model may be developed. Clearly, this approach to logic model development places it on a more solid foundation than has heretofore been possible. Unfortunately, the scope of the present study did not permit further consideration of this aspect of logic model development.

The fact that the human operator responds somewhat mechanically to the roll axis of an artificial horizon display has certain interesting implications. In producing this mechanical response, the human operator's task workload is reduced considerably. Variations in intersubject response also appear to be lessened. It would therefore seem advisable to undertake a study to develop procedures for designing display-controller systems which will allow this mechanical type of response on the part of the human operator. With a system designed by this procedure, the human operator would be able to handle more complex tasks or more numerous tasks because of the workload-reducing effect of these systems. Moreover, a designer could expect smaller variations in the system's responses for various human operators.

The method for modeling the human operator on a time-varying basis, which was proposed in Chapter IV at the end of the section on response rules, is certainly worthy of investigation. As stated earlier, there are strong indications that the human operator's time-variability is a result of biologically oriented phenomena. Accordingly, statistical methods should be developed to describe this time-variation, since it is not related to the signals

in the control system. It would then be possible to develop a statistical-dynamical model of a "typical" human operator even though the response of any given operator was not matched in time.

A very important problem in manual control system design is the determination of the weighting that the human operator places on error and on control action. It is known that pilots track in somewhat differing ways. This difference may be the result of the pilot's selection of a certain importance measure. It is suggested that this problem be studied in detail since it has bearing on synthesis procedures for manual control. A preliminary derivation has already been developed at CAL (under internal research) which shows the feasibility of measuring the pilot's performance measure.

Finally, those of us who have worked on this project are becoming increasingly aware of a fundamental problem in manual-control design. It is the problem of a complete lack of synthesis methods for manual control systems. At best, trail-and-error methods of manual control system design are available for only the simplest control systems. If a multiloop or a multiaxis manual control system is to be designed, no adequate design procedures are available. It would seem that serious consideration should be given to the use of more advanced models of the human operator in development of true mathematical synthesis methods for manual control systems.

## Review of Recommendations

- 1) Determine the true remnant and true time variations in transfer characteristics for an ensemble of subjects.
- 2) Determine the best constraint setting value for time-variation when the deterministic theory is used.
- 3) Develop a simpler logic model by means of the nonlinear deterministic theory.
- 4) Develop a new type of display-hand controller combination that allows "mechanical responses" based on geometrical relationships.
- 5) Determine a statistical model for the time-variations in the human operator's transfer characteristic.
- 6) Develop and verify methods for determining the human operator's selection of a performance measure.
- 7) Develop a method of synthesis for complex manual control systems.

## VII. REFERENCES

1. Wierwille, W.W., and Gagne, G.A., "A Theory for the Optimal Deterministic Characterization of the Time-Varying Dynamics of the Human Operator," NASA Report CR-170, Washington, D.C., February, 1965.
2. Wierwille, W.W., "A Theory for Optimal Deterministic Characterization of Time-Varying Human Operator Dynamics," IEEE Trans. HFE, Vol. HFE-6, No. 1, September 1965.
3. Elkind, J.I., Starr, E.A., Green, D.M., and Darley, D.L., "Evaluation of a Technique for Determining Time-Invariant and Time-Variant Dynamic Characteristics of Human Pilots," NASA Tech. Note. D-1897, Washington, D.C., May 1963.
4. Potts, T.F., Ornstein, G.N., and Clymer, A.B., "The Automatic Determination of Human and Other Parameters," Proc. Western Joint Computer Conf., May 1963 (Los Angeles, Calif.), pp. 645-660.
5. Adams, J.J. and Bergeron, H.P., "Measured Variation in the Transfer Function of a Human Pilot in Single Axis Tasks," NASA Tech. Note D-1952, October 1963.
6. McRuer, D. et. al., "Human Pilot Dynamics in Compensatory Systems," AF Flight Dynamics Lab. Rpt. No. AFFDL-TR-65-15, July, 1965.
7. Elkind, J.I., "Characteristics of Simple Manual Control Systems," MIT, Lincoln Laboratory, TIP-111, April 1956.
8. Hall, I.A.M., Effects of Controlled Element on the Human Pilot, WADC Technical Report 57-509, August 1958.
9. Bekey, G.A., Meissinger, H.F., and Rose, R.E., Mathematical Models of Human Operators in Simple Two-Axis Manual Control Systems, IEEE Trans. HFE, Vol. HFE-6, No. 1, September 1965.
10. Fryer, W.D., and Schultz, W.C., A Survey of Methods for Digital Simulation of Control Systems, CAL Report No. XA-1681-E-1, July 1964.
11. Shannon, C.E., Communication in the Presence of Noise, Proc. Inst. of Radio Engrs., Vol. 37, January 1949.

*"The aeronautical and space activities of the United States shall be conducted so as to contribute . . . to the expansion of human knowledge of phenomena in the atmosphere and space. The Administration shall provide for the widest practicable and appropriate dissemination of information concerning its activities and the results thereof."*

—NATIONAL AERONAUTICS AND SPACE ACT OF 1958

## NASA SCIENTIFIC AND TECHNICAL PUBLICATIONS

**TECHNICAL REPORTS:** Scientific and technical information considered important, complete, and a lasting contribution to existing knowledge.

**TECHNICAL NOTES:** Information less broad in scope but nevertheless of importance as a contribution to existing knowledge.

**TECHNICAL MEMORANDUMS:** Information receiving limited distribution because of preliminary data, security classification, or other reasons.

**CONTRACTOR REPORTS:** Technical information generated in connection with a NASA contract or grant and released under NASA auspices.

**TECHNICAL TRANSLATIONS:** Information published in a foreign language considered to merit NASA distribution in English.

**TECHNICAL REPRINTS:** Information derived from NASA activities and initially published in the form of journal articles.

**SPECIAL PUBLICATIONS:** Information derived from or of value to NASA activities but not necessarily reporting the results of individual NASA-programmed scientific efforts. Publications include conference proceedings, monographs, data compilations, handbooks, sourcebooks, and special bibliographies.

*Details on the availability of these publications may be obtained from:*

SCIENTIFIC AND TECHNICAL INFORMATION DIVISION  
NATIONAL AERONAUTICS AND SPACE ADMINISTRATION  
Washington, D.C. 20546